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Final Report

MULTISPECTRAL SCANNER DATA APPLICATIONS EVALUATION

Volume I — User Applications Study

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16. Abstract

A six-month systems study (Contract NAS9-13386, CCA2; Multispectral Scanner Data Applications Evaluation) of earth resource surveys from satellites was conducted and is reported in two volumes. SKYLAB S-192 Multispectral Scanner (MSS) data were used as a baseline to aid in evaluating the characteristics of future systems using satellite MSS sensors. The study took the viewpoint that overall system (sensor and processing) characteristics and parameter values should be determined largely by user requirements for automatic information extraction performance in quasi-operational earth resources surveys, the other major factor being hardware limitations imposed by state-of-the-art technology and cost.

The objective was to use actual aircraft and spacecraft MSS data to outline parametrically the trade-offs between user performance requirements and hardware performance and limitations so as to allow subsequent evaluation of compromises which must be made in deciding what system(s) to build. The analysis was conducted with the realization that these compromises might be different for different missions and systems.

17. Key Words
Automatic Data Processing
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FOREWORD

This report describes part of a comprehensive program concerned with advancing the state-of-the-art in remote sensing of the environment from aircraft and satellites. The research was carried out for NASA's Lyndon B. Johnson Space Center, Houston, Texas, by the Environmental Research Institute of Michigan (ERIM), Ann Arbor, Michigan, and by Honeywell Radiation Center, Lexington, Massachusetts.

The Multispectral Scanner Data Applications study consisted of two tasks: Task I, the User Applications Study reported herein; and Task II, a Sensor Systems Study reported in volume II. The integrated results of Tasks I and II are presented in an Executive Summary, published as a separate document.

Substantial contributions of written material for this volume of the report were made by: J. Braithwaite, R. Dillman, W. Malila, B. Salmon, N. Roller, and F. Sadowski.

The work of the following staff members on the User Applications Study is also appreciated: T. Austin, C. Bennett, A. Kerber, D. Rebel, R. Turner, D. [illegible]rbassik, W. Pillars, and C. Wezernak.

Ground observation data were graciously made to us by Professors L. Manderscheid and E. Safir, Michigan State University, for the Michigan Agricultural Site; Dr. R. Alexander USDI/USGS, for the Baltimore Land Use Site; and Dr. R. Cartmill, NASA/MTF/ERL, for the Atchafalaya Test Site.

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INTRODUCTION AND SUMMARY

1.1 PURPOSE

A number of attempts have been made to establish multiple discipline user data requirements for earth resources data acquisition systems. Previous results have been unsatisfactory, primarily because of the very limited experience of the users with the developing technology and the paucity of hard data of adequate quality and relevance on which to base firm analytic studies. As a result of the Skylab S191 and S192 programs, the ERTS program, and data collected by several airborne multispectral scanners, however, an extensive base of such hard data now exists.

The purpose of this study was to use actual MSS data to outline parametrically the trade-offs between user performance requirements and hardware performance and limitations so as to allow subsequent evaluation of compromises which must be made in deciding what system(s) to build.

1.2 SCOPE

The study (Contract NAS9-13386, CCA2; Multispectral Scanner Data Applications Evaluation) was conducted during the period January 1, 1974 through June 30, 1974 and is reported in two volumes. Skylab S192 Multispectral Scanner (MSS), and Ancillary Aircraft Scanner data were used in evaluating the characteristics of projected future MSS systems. The study took the viewpoint that overall system (sensor and processing) characteristics and parameter values should be determined largely by user requirements for automatic information extraction performance in quasi-operational earth resources surveys (the other major factor being hardware limitations imposed by state-of-the-art technology and cost).

1.3 APPROACH

The approach consisted of a User Applications Study (Task I, reported herein) and a Sensor System Study (Task II, reported in Volume II of this report). In the User Applications Study, S192 and Ancillary Aircraft Scanner data (collected as nearly simultaneously as possible) were machine processed with the ancillary data simulating data from various possible satellite MSS sensors of varying characteristics to obtain automatic information extraction performance results in four important disciplines: agriculture, urban land use, geology, and water and marine studies. A prime requirement was the availability of good quality, cloud free, MSS data from S192 and aircraft, and at least adequate ground information. The empirical results obtained were augmented by critical reviews of existing literature, and by ERIM's experience in working with user applications. The effects of varying spectral bands, spatial resolution, and radiometric fidelity on the achievable classification performance were addressed in the User Applications Study.

In the Sensor Systems Study, parametric curves for several critical variables were derived to allow trade-off analysis and assessment of impact of user requirements on sensor feasibility, high risk technology areas and hardware cost. This task was performed under subcontract by the Honeywell Radiation Center (HRC), Lexington, Massachusetts.

The two studies interact to produce an assessment of feasible hardware characteristics capable of meeting the user data requirements with an acceptable level of technological risk at costs which are not excessive.

1.4 RESULTS

Based upon the results discussed in Section 3 through 5, and Appendices A and B of this report, the following conclusions and recommendations based upon these conclusions are presented:

Spectral Study

A thematic mapping system equipped with optimum spectral bands required by users in all disciplines would require an unacceptable level of cost and technological risk. (Within an acceptable range of other system parameters.) In view of this conclusion, the spectral bands listed below are recommended to support missions optimized for Agriculture, Urban Land Use, and Water Resources investigations.

- 0.45-0.52 μm
- 0.52-0.60 μm
- 0.63-0.69 μm
- 0.80-0.95 μm
- 1.55-1.75 μm
- 10.4-12.5 μm
- 0.42-0.48 μm or 8.3-9.3 μm

Radiometric Study

With the exception of some of the specifications desired by Water Resources and Marine and Oceanographic users, radiometric requirements can be met with an attendant acceptable cost and level of technological risk. The results presented in Section 5 of this report dictate the radiometric specifications listed below.

- $NE\Delta\rho$ for reflective bands - 0.5% *
- $NE\Delta T$ for thermal bands - 0.5°K
- Maximum allowable gain variation - 1.4% of full scale
- Maximum allowable offset variation - 0.38% of full scale
- Automatic Gain Control to provide the recommended $NE\Delta\rho$ and $NE\Delta T$ for reflectances ranging from 2.0% to 60.0% and Temperatures ranging from 260°K to 340°K

*The recommended $NE\Delta\rho$ is based upon the data presented in Tables 4-8 through 4-11. Empirical results do not support this recommendation for the reflective IR portion, due to the uncertainties in the IR data bands.

Spatial Study

Little improvement in classification accuracy and area estimation will be realized in Agriculture and Urban Land Use disciplines for a spatial resolution finer than 30 meters. Study results do indicate, however, appreciable degradation in classification accuracy as spatial resolution is coarsened from 30 meters to 60 meters. Since the effect of resolutions between 30 meters and 60 meters upon classification accuracy was not investigated, a precise spatial resolution is not recommended. Pending further study the recommended spatial resolution is 30 meters to 60 meters.

2
APPROACH

2.1 GENERAL

The study approach was organized into two tasks. Task I, User Applications Study was to analyze S192 and aircraft scanner data sets collected as nearly simultaneously as possible, and to supplement the results thus obtained with a critical review of existing literature and theoretical results in an effort to quantify the effects on automatic classification accuracy by varying sensor parameters. Four sites were selected, each representing a specific user discipline such as Agriculture or Urban Land Use. A second prime requirement for selecting these sites was the availability of both airborne and spaceborne multispectral scanner data and adequate ground observation data. The available data were processed to determine the ways in which data quality factors such as spatial and spectral resolution influence the accuracy of processed outputs such as crop identification or acreage measurements.

In the second task, Sensor System Study, reported in Volume II, the available performance of several types of orbital scanners were parametrically studied. For each approach, trade-off studies were undertaken to find ways in which high risk technology could be avoided at minimum cost to performance parameters.

Finally, the two tasks were integrated to demonstrate the extent to which realistic user requirements could be met by various orbital acquisition systems and supporting telemetry and ground processing systems. Further, the reduction in data utility for the several classes of users by reducing system performance to minimize cost and technological risk were studied. The results were organized to facilitate selection of an optimum data acquisition system for a variety of constraints, such as limited development time or changed relative priorities among user goals.

The effects of varying number of spectral bands, spectral band placement, spatial resolution, and radiometric accuracy on the performance of proven earth resources classification and parameter estimation algorithms for various user disciplines were determined. Because of time and funding constraints processed examples were not generated for each discipline by varying each of the four parameters discussed above. Rather, the approach was to select examples which critically influence the selection of spectral bands, spatial resolution, and radiometric parameters. Further, the suggested processing effort was supplemented by a review of appropriate literature (especially on the subject of optimum spectral bands), and by close coordination with efforts at NASA-ERL to determine optimum spectral bands.

In studies of radiometric accuracy, where these parameters were varied and the effect on extractive processing algorithms demonstrated, Sensor Systems Study personnel (Task II) suggested the reasonable variations to make in the sensor parameters. This insured that the simulated cases were reasonable and achievable within current and projected hardware technology.

In studies of spatial resolution effects, attempts were made to simulate the 10, 30, and 60 meter resolutions currently being considered for advanced spacecraft instrumentation. A theoretical calculation on the effect of resolution element size in determining field acreages for various size and shape fields was also performed.

To assist in determining the effects of varying system parameters on the performance of established classifier algorithms, subcontract support was solicited from Honeywell Corporation, Minneapolis, Minnesota. Rather than generate processed data products and tables of performance from multispectral data sets, Honeywell studied the feasibility of using their "information model" to predict the performance of a classifier without actually classifying data. A comparison

of the classifier approach and the "information model" approach was conducted for the Land Use case study.

2.2 PROCESSING

2.2.1 MICHIGAN TEST SITE (AGRICULTURE)

2.2.1.1 General

The purpose of processing data from the Michigan Test Site was to obtain further information about the optimum spectral bands to be used for classifying agricultural scenes, and to demonstrate the effects of spatial resolution and radiometric variation on classification accuracy. Aircraft data sets were processed for this phase of the study. Characteristics of the data used for this segment of the study are shown in Table 2-1. The S192 data processing and analysis approach is discussed in Appendix C.

2.2.1.2 Aircraft Data

The first step in processing the aircraft data was to generate the 28.7 m and 57.2 m resolution data sets from the basic 14.3 m data by smoothing. (Hereafter these spectral resolutions are referred to by their nominal values — 15, 30 and 60 meters.) Following smoothing, three data sets were processed similarly to prepare recognition maps of terrain categories and to evaluate performance.

First a map of a red band was prepared for each data set to permit locating training sets and verifying data coverage. Then statistics for 3-5 fields of each agricultural crop to be recognized were extracted from the data. The 30 m data map was used to select training sets as a test of the ease of locating these sets on imagery of that resolution. Training set locations were then transferred to the other data sets. This was done without plotting the training sets on the other graymaps because the 30 and 60 m data sets were derived (by smoothing) from the 15 m data, and thus line and point numbers bore a known relationship between data sets.

TABLE 2-1. DATA CHARACTERISTICS

Michigan Ancillary Data

Project 102806 - Contract NAS9-13386

SPECTRAL CHANNELS AVAILABLE

.41 - .48 μm	.58 - .64
.46 - .49	.62 - .70
.48 - .52	.67 - .94
.50 - .54	1.0 - 1.4
.52 - .57	1.5 - 1.8
.55 - .60	9.3 - 11.7

SPATIAL RESOLUTION CASES CONSIDERED

14.3 meters

28.7 meters

57.2 meters

OTHER PERTINENT DATA

Date of Collection:	5 August 1973
Flight Altitude:	10K ft above terrain
Sensor:	ERIM M-7 MSS
Time of Day:	1421 - 1433 GMT
Quantity of Data:	3 x 24 miles

Following an analysis of signatures, the signatures for the same crop type were combined to form a composite signature for recognition. The composite signatures were fed to the channel selection algorithm which selected the seven optimum channels for further analysis. In the process, the utility of all channels was determined and the channels were ordered by increasing utility in separating the signatures. Next the data were classified using the signatures and the optimum twelve, seven, and four channels. The classified results were displayed, and test sets analyzed to determine accuracy of field acreage estimation by crop types. The flow of operations for this segment of the processing of agriculture data is shown in Figure 2-1.

Figure 2-2 shows the flow of processing operations for the radiometric study of agriculture aircraft scanner data. The approach was to obtain signatures from radiometrically correct data, then classify radiometrically degraded data. As shown in Figure 2-2, two cases of radiometric degradation were explored for each of the three parameters. The radiometrically "correct" raw data set constituted a third case for each parameter.

Thirty meter resolution, angle corrected data from the aircraft scanner were processed for this study. The data were degraded by artificially inducing two levels of offset, gain slope, and noise to the original data. The quantizing accuracy of the data was adjusted as the noise was varied, and 9, 8, 7, 6, and 5 bit cases were considered, with noise levels matched to the digitization precision. Gain slope and offset variations of $\pm$ 33% and $\pm$ 66% of average signatures separation of mapped classes were also introduced. Each variation constituted a separate data set for processing. The optimum seven spectral channels were used in the classification of data.

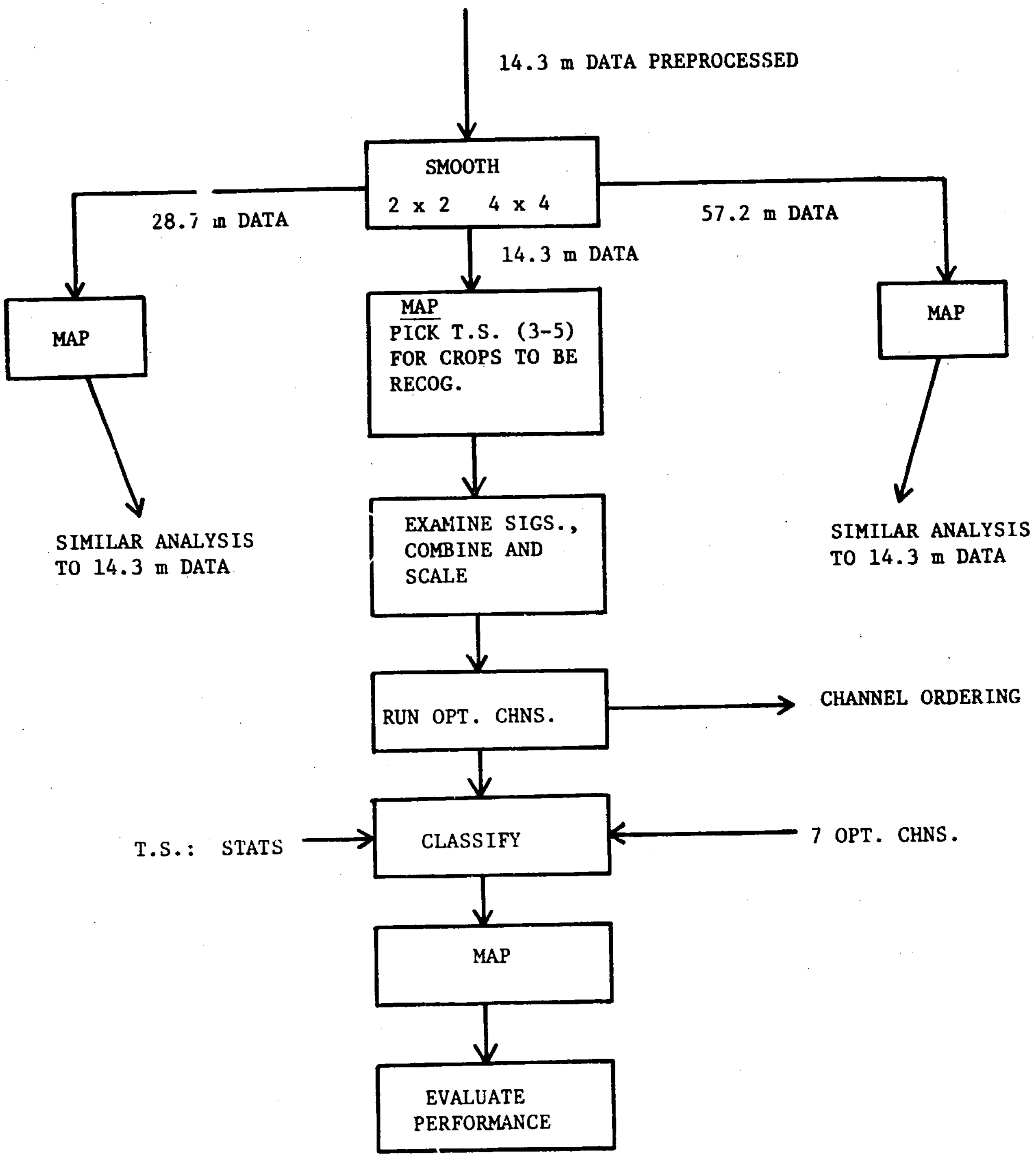


FIGURE 2-1. FLOW OF PROCESSING FOR AGRICULTURE CASE STUDY

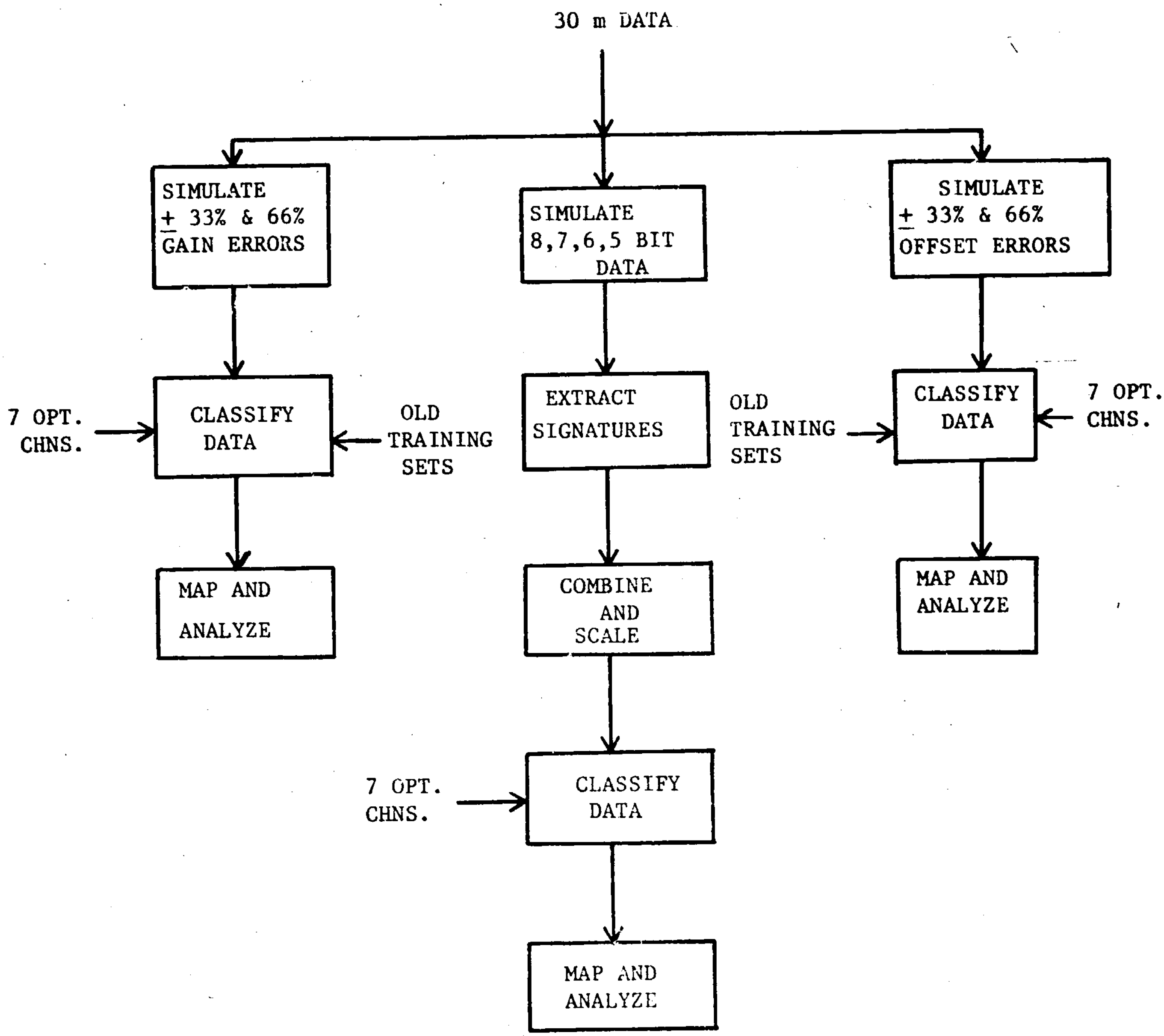


FIGURE 2-2. PROCESSING AND ANALYSIS FLOW - RADIOMETRIC STUDIES

2.2.2 WHITE SANDS TEST SITE (GEOLOGY)

2.2.2.1 General

Skylab S192 data and NASA 24 channel scanner (MSDS) data collected over White Sands, New Mexico were used for the geology discipline study. The aircraft data characteristics are shown in Table 2-2. These data were processed (see Figure 2-3) to ascertain the optimum spectral bands and to determine the effects of variation of the number of spectral bands on geologic classification accuracy. The S192 data processing and analysis approach is discussed in Appendix C.

2.2.2.2 Aircraft Data

The basic 6 m resolution MSDS data was smoothed by 5 to simulate 30 m resolution data. Next a graymap of the red band was prepared for location of training sets and verification of data coverage and quality. Using ground information gathered from geologic maps and past geologic studies, training sets for important rock and soil types in the White Sands Area were located on the graymap.

Before signatures were extracted for the geologic materials, a set of promising ratio features were defined by analysis of Earth Resources Spectral Information System (ERSIS) data of the materials likely to be found in the scene. ERSIS library spectra were then edited using standard editing programs, to yield spectra of materials likely to be in the scene. A set of likely materials was then determined from analysis of ground truth information. Of 98 possible ratios, twenty promising ratios were defined by calculating reflectance ratio data from ERSIS (band averaged over MSDS spectral bandwidths), and selecting ratios which separate the scene materials in ERSIS.

When the twenty promising ratios were identified, signatures from the training sets, previously located on the graymap, were extracted. A transformation routine was then used to calculate ratio feature

TABLE 2-2. DATA CHARACTERISTICS

White Sands Ancillary Data

SPECTRAL CHANNELS AVAILABLE

MSDS Chan #	Bandwidth	MSDS Chan #	Bandwidth
1	.34 - .40	11	1.18 - 1.30
2	.40 - .44	*12	1.52 - 1.73
3	.46 - .50	13	2.10 - 2.36
4	.53 - .57	17	8.30 - 8.80
5	.57 - .63	19	9.30 - 9.80
6	.64 - .68	20	10.10 - 11.00
7	.71 - .75	21	11.00 - 12.00
8	.76 - .80	22	12.00 - 13.00
9	.82 - .87	*23	1.12 - 1.16
10	.97 -1.05	*24	1.05 - 1.09

SPATIAL RESOLUTION CASES CONSIDERED

30 m

OTHER PERTINENT DATA

Date of Collection:	22 February 1974
Flight Altitude:	(9800 - 12,000 ft actual) requested 10,000 ft
Sensor:	MSDS
Time of Day:	1719 - 1746 GMT
Quantity of Data:	3 runs, 2.6 x 24 mi. total

*Noisy data per mission flight logs.

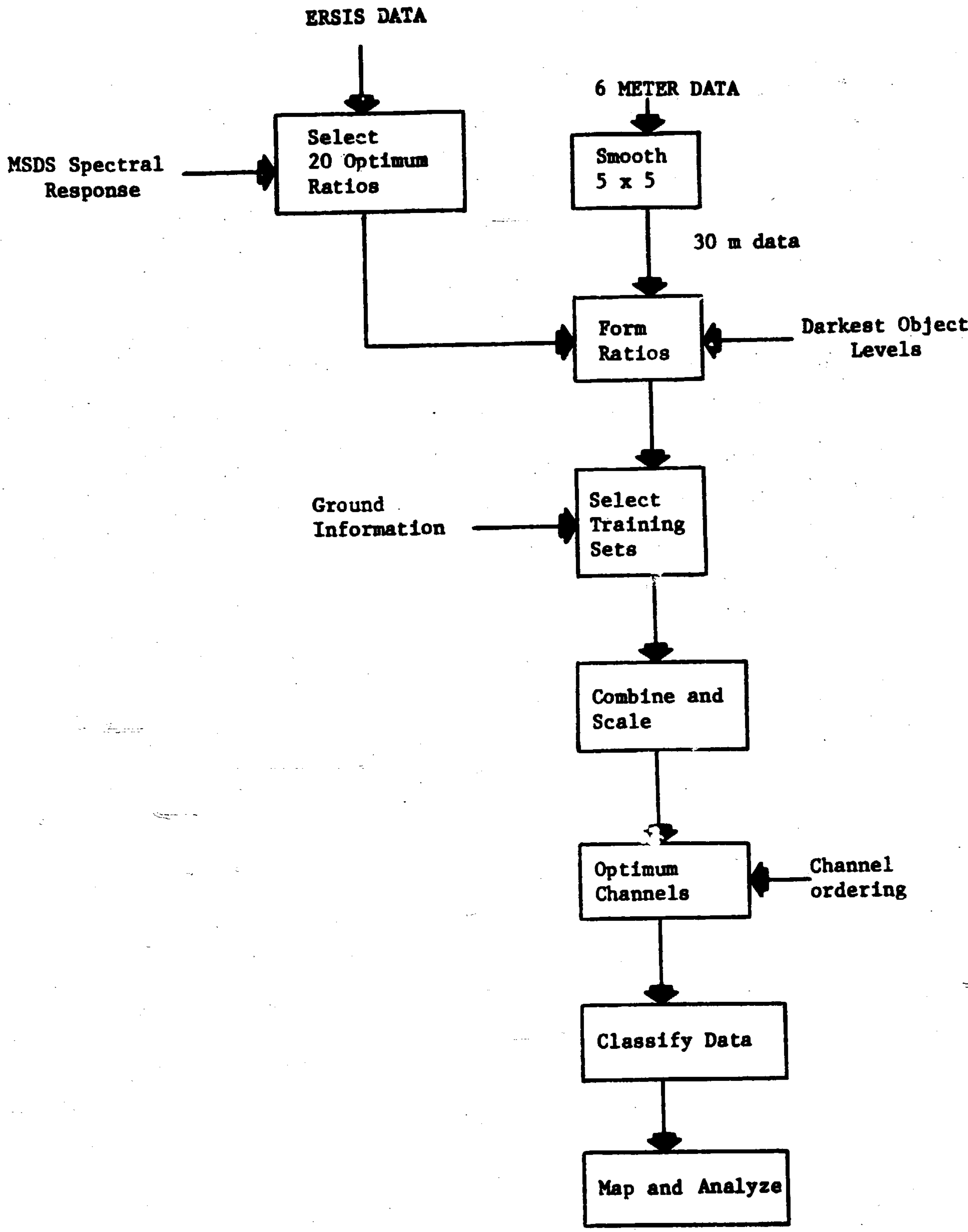


FIGURE 2-3.PROCESSING FLOW FOR WHITE SANDS AIRCRAFT DATA

signatures directly. Before forming the ratio features for signature calculation, the darkest object level was subtracted from each signal value in the channels to be divided.

Signatures extracted from the training sets were then analyzed for consistency, and signatures of like materials combined to form training set statistics more characterisic of the class to be recognized. The optimum ratio features, and the spectral channels comprising these ratios were prioritized by the feature selection program.

Data was then classified, using the composite training set statistics, the optimum 15, 7, or 5 spectral channels, and the darkest object levels previously determined in preprocessing. Recognition maps were displayed and analyzed to determine the correct and incorrect classification of geologic materials.

2.2.3 BALTIMORE TEST SITE (LAND USE)

2.2.3.1 General

The purpose of the processing of the data from the Baltimore Test Site was to obtain further information about the optimum spectral bands to be used for classifying urban land use categories to Levels I and II of the Anderson Land Use Classification System and Level III of the State of Maryland Land Use Classification System to demonstrate the effects of radiometric variation on classification accuracy. Both S192 and aircraft scanner data sets were processed for this phase of the study. Characteristics of the data used for this segment of the study are shown in Table 2-3. All processing of S192 data for the Baltimore Test Site was conducted by Honeywell and is detailed in Appendix C.

TABLE 2-3. DATA CHARACTERISTICS

Baltimore Ancillary Data

SPECTRAL CHANNELS AVAILABLE

M-7 Channels

.41 - .49 μm	.55 - .60	2.0 - 2.6
.46 - .49	.58 - .64	9.3 - 11.7
.48 - .52	.62 - .70	
.50 - .54	.57 - .94	
.52 - .57	1.0 - 1.4	

SPATIAL RESOLUTION CASES CONSIDERED

7.2 meters
14.4 meters
28.8 meters
57.6 meters

OTHER PERTINENT DATA

Date of Collection:	11 May 1972
Flight Altitude:	5000 ft above terrain
Sensor:	ERIM M-7 scanner
Time of Day:	1745 GMT
Quantity of Data:	2 x 25 miles

2.2.3.2 Aircraft Data

Figure 2-4 details the processing flow for the study to determine the ordering of spectral channels for land use classification. The first step in processing was to smooth data, averaging 4 x 4 to yield a data set simulating 30 meter resolution. A red channel map was made to facilitate selection of training sets and to validate data quality.

Using USGS-supplied ground information, training sets were selected from all Level I and II land use types. This step was augmented by Level III and IV ground truth obtained from the Maryland State Planning Division and from photointerpretation. Five samples of each type of land use were selected to more completely span the range of variability of the land use types. The selection of these training sets was to be coordinated with Honeywell personnel at Minneapolis, who carried out related studies.

Signatures were extracted for each training set sample. After examination of the signatures to determine any anomalies, the signatures representing the same land use class were combined and scaled. Combined signatures for each class were then fed to the optimum channel program to determine the order of spectral channels in classifying land use types. Optimum four and seven channels were then identified and used to classify data. All spectral channels available were also used to study the effects of number of spectral channels on classification accuracy.

The processing approach used in demonstrating the effect of radiometric variations on classification accuracy was identical to the approach detailed in Section 2.2.1.2 and shown in Figure 2-2.

2.2.4 ATCHAFALAYA TEST SITE (WATER AND MARINE)

2.2.4.1 General

The purpose of processing data from the Atchafalaya test site was to obtain further information on optimum spectral bands to be used

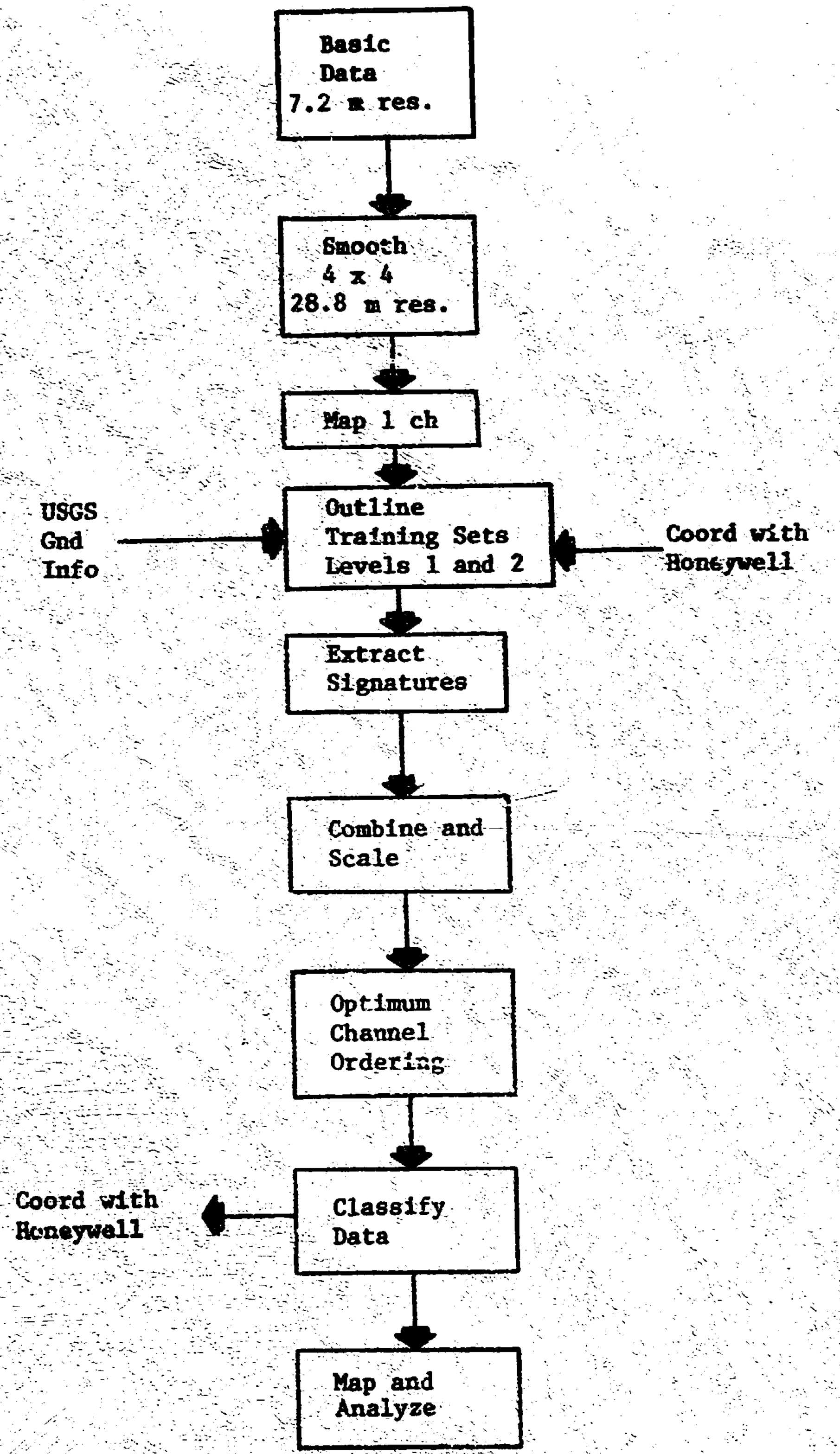


FIGURE 2-4. PROCESSING FLOW FOR BALTIMORE AIRCRAFT DATA

for mapping turbidity (both organic and inorganic), current patterns and natural coastal vegetation communities which may influence the aquatic ecosystem. The MSDS data collected is outlined in Table 2-4.

2.2.4.2 Aircraft Data

MSDS data was processed according to the general flow diagram of Figure 2-5. Aircraft data at 12 meters resolution was smoothed by 2 to approach a nominal 30 meter resolution size. Training sets for organic and inorganic turbidity differences along with vegetation were selected and signatures computed. The signatures were analyzed and the optimum channels to use for turbidity and current mapping selected. The optimum single channels were then used to select channels for ratioing in order to map organic turbidity and natural vegetation communities.

Single channel and ratioed graymaps were produced and analyzed.

2.3 HONEYWELL APPROACH TO SPECTRAL-SPATIAL FEATURE CLASSIFICATION

At Honeywell-Minneapolis, investigators used aircraft scanner data from the Baltimore Test Site for a study of the classification accuracy of Land Use categories using a K-Class classifier and spectral and spatial features. The spectral features used were the seven optimum features selected by ERIM from an analysis of spectral signatures of a number of land use classes. Spatial features, representing the energy in the scene at particular spatial frequencies, were generated as discussed below. Then a number of classification and channel ordering runs were made on the data and the results evaluated.

2.3.1 GENERATION OF SPATIAL FEATURES

The spatial features used in this study were generated by taking the Fourier Transform of the data, followed by mathematical manipulations to create features that were "rotationally invariant".

TABLE 2-4. DATA CHARACTERISTICS

Atchafalaya Ancillary Data

SPECTRAL CHANNELS AVAILABLE

.34 - .40 μm	1.18 - 1.30	1.12 - 1.16
.40 - .44	1.52 - 1.73	1.05 - 1.09
.46 - .50	2.10 - 2.36	
.53 - .57	3.54 - 4.00	
.57 - .63	4.50 - 4.75	
.64 - .68	6.00 - 7.00	
.71 - .75	9.30 - 9.80	
.76 - .80	10.10 - 11.00	
.82 - .87	11.00 - 12.00	
.97 - 1.05	12.00 - 13.00	

SPATIAL RESOLUTION CASES CONSIDERED

30 m

OTHER PERTINENT DATA

Date of Collection:	21 September 1973
Flight Altitude:	20,000 ft above terrain
Sensor:	MSDS, RC-8
Time of Day:	1631 - 1805 GMT
Quantity of Data:	2 Runs, each 5.3 x 40 n. mi.

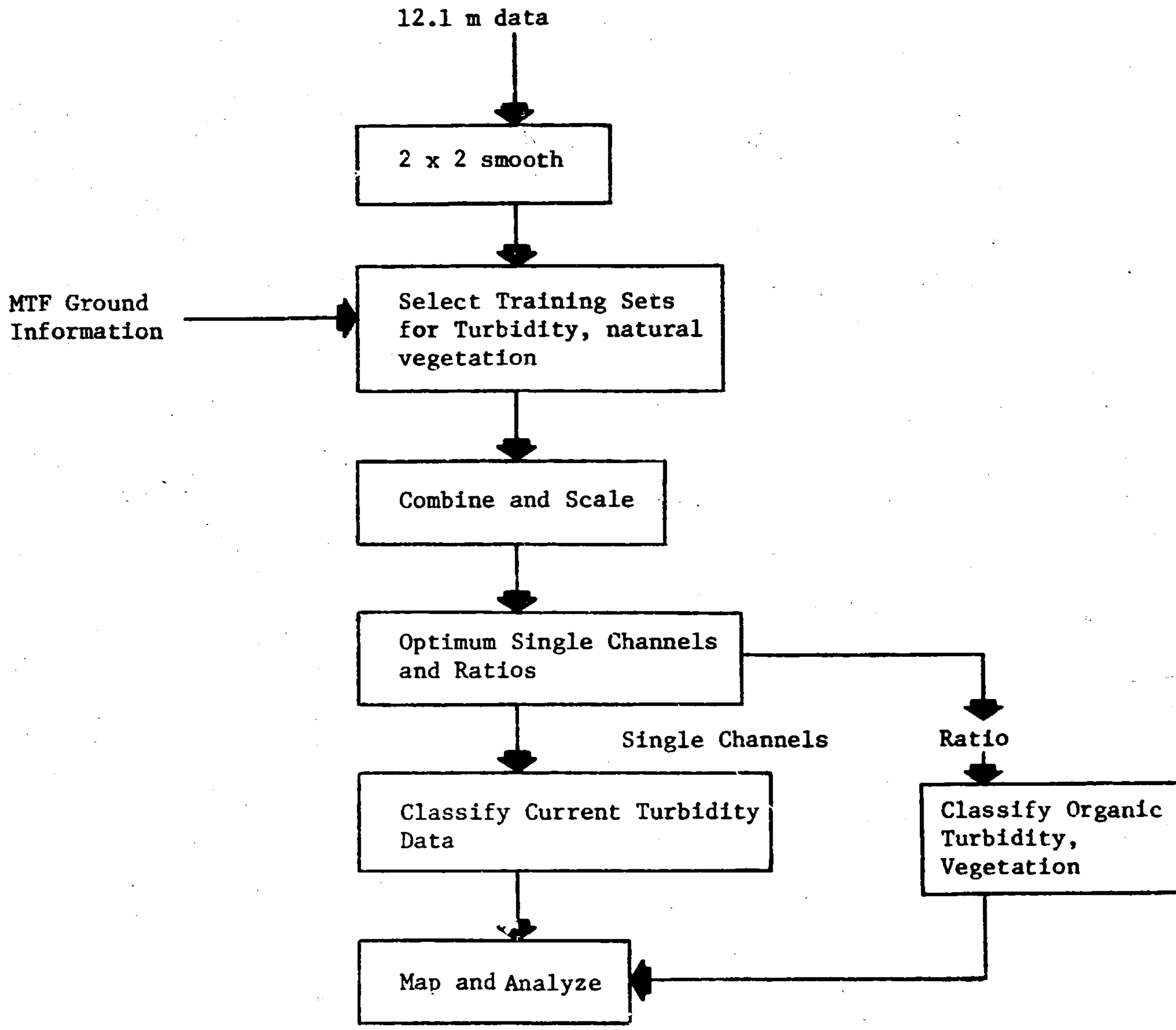


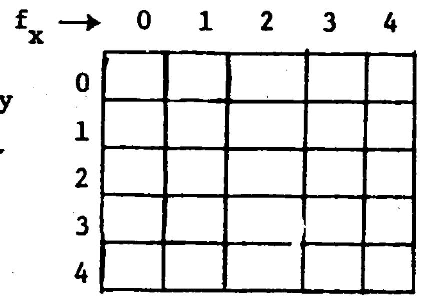
FIGURE 2-5. PROCESSING FLOW FOR ATCHAFALAYA AIRCRAFT DATA

By making the features rotationally invariant, the values of the spatial features for a square building would be the same regardless of the orientation of the building with respect to the scan line.

To generate the spatial features, the first eigenvector constructed from the seven optimum channels was used. This eigenvector contains the most variation of any spectral feature and was thus felt to be good for the generation of spatial features. Next the raw spatial features were formed by a Fourier Transform on 8 x 8 (56 x 56 m) arrays of points (4 x 4 arrays, still representing 56 x 56 m arrays, were used for the 14 m data). The choice of a 56 m array was arbitrary, and in retrospect, not entirely appropriate to this application. Subsequent data analysis for the Honeywell Information Model showed that most of the spatial information in the scene was contained in spatial frequencies lower than 1/56 m. Spatial features representing scene energy at these low frequencies could not be generated with the arrays of points chosen. The spatial features generated for the 7 m data and for the 14 m data are shown in Table 2-5. These rotationally invariant features were generated from the raw Fourier Transform data. In the nomenclature of Table 2-5, rotationally invariant features are denoted by B_0-B_5 and the raw Fourier Transformed data by (a,b). Fourier Transform feature (0,0) is the average energy in the 8 x 8 or 4 x 4 pixel block. For the 8 x 8 pixel block four spatial frequency components can be derived for each direction. These correspond to energy at 1/56 m, 1/42 m, 1/28 m, and 1/14 m, (0,1), (0,2), (0,3), and (0,4) respectively. Then the Fourier Transform data in the x and y directions were combined as shown to yield the "B" features actually shown in Table 2-5. For the 14 m data, the Fourier Transformed features (0,1), and (0,2) corresponded to energy at spatial frequencies of 1/56 m and 1/28 m respectively. They were combined as shown to yield the rotationally invariant "B" features.

TABLE 2-5. TEXTURAL FEATURE GENERATION

<u>8 x 8 PEL GRID</u> (5 x 5 SPATIAL FREQUENCY GRID)



B_o = (0,0)

B_1 = (1,0) + (0,1) + 0.65 (1,1)

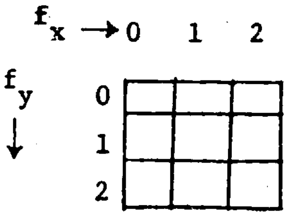
B_2 = (2,0) + (0,2) + 0.8[(2,1) + 1,2)]
+ 0.35(1,1) + 0.1(2,2)

B_3 = (3,0) + (0,3)
+ 0.9[2,1) + (1,3) + (2,2)]
+ 0.3[(3,1) + (1,3) + (2,2)]
+0.3[(3,2) _ (2,3)] + 0.2[(2,1) + (1,2)]

B_4 = (4,0) + (0,4) + (4,1) + (1,4) + 0.35[(4,2) + (2,4)]
+ 0.7[(3,2) + (2,3)] + 0.1[(3,1) + (1,3)] + 0.8 (3,3)

B_5 = 0.65[(4,2) + (2,4)] + (4,3) + (3,4) + (4,4) + 0.2 (3,3)

<u>4 x 4 PEL GRID</u> (3 x 3 SPATIAL FREQUENCY GRID)



B_o = (0,0)

B_1 = (0,1) + (1,0) + 0.65 (1,1)

B_2 = (0,2) + (2,0) + (1,2) + (2,1)
+ (2,2) + 0.35 (1,1)

2.3.2 CLASSIFICATION PROCEDURE

Several classification runs were made with the spectral and spatial features on 7, 14, and 56 m data. In summary, these are listed in Table 2-6. Class designations for each of these runs are listed in Table 2-7. The intent of the classification was to demonstrate what spatial features added to the classification accuracy of urban land use classes at various spatial resolutions. Also, results using simulated 56 m data demonstrate the effect of varying numbers of channels on the ability to separate Level III land use classes.

2.4 LITERATURE SURVEY

To augment and extend the empirical results obtained during this study, a review was performed of all published literature detailing the optimum spectral bands for each discipline. The review was confined to publications which were directed at obtaining optimum spectral bands for a given investigation. Previous empirical analysis and theoretical publications were surveyed for each discipline and three previously conducted systems studies were cited for all disciplines. Results of the literature survey are presented in Section 3.

TABLE 2-6. BALTIMORE SPECTRAL/SPATIAL FEATURES GENERATED BY HONEYWELL

1.	7 m data	7 spectral, 6 spatial features
2.	14 m data	7 spectral, 3 spatial features
3.	14 m data	7 spectral features
4.	14 m data	7 best features (6 spectral, 1 spatial)
5.	56 m data	7 spectral features
6.	56 m data	4 spectral features
7.	56 m data	2 spectral features

Note: Fifteen Level III training sets, as shown in Table 2-7, were used for this analysis.

TABLE 2-7. CLASS DESIGNATIONS FOR BALTIMORE DATA SETS

Description	ERIM Class	Honeywell Designation
Residential, Single Family	111	1
Residential, Multiple Family	112	2
Commercial, Retail	121	3
Industrial, Wholesale/Light Ind.	122	4
Industrial, Metal	132	5
Industrial, Chemical	134	6
Transportation, Railroads and Yards	152	7
Transportation, Freeways/Highways	153	8
Transportation, Marine Terminals	154	9
Transportation, Utilities	155	10
Institutional	160	14
Institutional, Secondary Schools	162	11
Institutional, Colleges	163	12
Institutional, Military Installations	164	13
Institutional, Other (e.g., Hospitals)	165	14
Open/Other (Urban Parks, Recreational)	190	15

3
SPECTRAL REQUIREMENTS STUDY

3.1 GENERAL

The spectral study addressed the selection of optimum spectral bands for each discipline and the determination of the effect of the number of spectral bands upon classification accuracy for representative disciplines. At the study's inception, it was felt that spectral band selection would depend on the application. Optimum bands for the Agriculture, Geology, Land Use, and Water and Marine test sites were selected by processing algorithms as described in Section 2, Task I. Classification was then conducted using the optimum 12, 7, and 4 spectral bands from these prioritized lists of bands for Agriculture and Land Use, and the optimum 15, 7, and 5 bands for Geology to assess the effect on classification accuracy. The empirical study alone, however, was inadequate to allow conclusions as to the optimum bands or the effect of the number of bands on classification accuracy for a given discipline.

The empirical results were compromised, first of all, by the fact that the selection of optimum bands for each discipline was made from a limited set of spectral bands available in present instrumentation (see Section 2). Proper empirical selection was further compromised by the fact that, while a band may have been available, it was not selected as an optimum band because it was noisy. In addition, the test site data used did not encompass all anticipated disciplinary objectives. The empirical channel selection from the agriculture test site, for example, was based only upon the availability to classify various types of vegetation and soil. The bands selected would likely have differed if an attempt had been made to assess such parameters as plant vigor and soil moisture content.

In view of the above qualifications on the empirical results, a literature survey was conducted, and the results of this survey were analyzed in an attempt to pinpoint the optimum precise location and bandwidths for each discipline in the spectral region 0.3-15 μm. The theoretical results were also used with results of the sensor performance analysis to make our final band selection. The reader will be able to trace the argument for the final band selection in each discipline.

3.2 AGRICULTURE/RANGE/FORESTRY

The optimum bands selected for the Michigan Agriculture test site are shown in Table 3-1. As shown in the table, the bands were prioritized by the STEPLIN Program [26] for simulated 15 m, 30 m, and 60 m resolutions which resulted in some variation in band selection and priorities. The variations are a result of signature extraction of the various resolutions. The smoothing technique used to simulate these resolutions necessarily produced changes in signature covariances for the agricultural scenes, hence, changes in the average pairwise probability of misclassification for the spectral bands. As can be seen in Table 3-1, however, channels 6, 8, 9, 11, and 12 were among the optimum seven channels selected for all simulated resolutions. In addition to these consensus bands, channels 1, 3, and 10 were each selected among the optimum seven channels in two of the simulated resolution cases.

Figure 3-1 is a graphic presentation of the performance results shown in Tables 3-2, 3-3, and 3-4 for the Michigan Agriculture data set using the optimum 12, 7, and 4 spectral channels for the simulated 30 m resolution case. As indicated in the figure, little or no improvement is seen in classification accuracy of five vegetative classes as the number of spectral channels is increased beyond four, and some of the vegetative classes show a decline in classification

TABLE 3-1. OPTIMUM CHANNELS FOR 15, 30, and 60 METER DATA SETS
MICHIGAN AGRICULTURE TEST SITE

ORDER OF SELECTION	15 METER DATA			30 METER DATA		60 METER DATA	
	CHANNEL NUMBER	(Wavelength Band)	AVERAGE PAIRWISE PROB. OF MISCLA.	CHANNEL NUMBER	AVERAGE PAIRWISE PROB. OF MISCLA.	CHANNEL NUMBER	AVERAGE PAIRWISE PROB. OF MISCLA.
1	8	(.62 - .70 μm)	.1137443	8	.1081104	8	.0893117
2	11	(1.5 - 1.8 μm)	.0286739	11	.0255942	11	.0202345
3	1	(.41 - .48 μm)	.0134848	1	.0110883	3	.0087382
4	9	(.67 - .94 μm)	.0095766	9	.0078789	12	.0052736
5	6	(.55 - .60 μm)	.0072649	6	.0054141	6	.0035129
6	12	(9.3 - 11.7 μm)	.0056775	10	.0041438	10	.0020811
7	3	(.48 - .52 μm)	.0046734	12	.0033340	9	.0015100
8	10	(1.0 - 1.4 μm)	.0039585	4	.0025448	4	.0012222
9	5	(.52 - .57 μm)	.0035252	3	.0022475	1	.0010751
10	4	(.50 - .54 μm)	.0033057	2	.0021041	2	.0010041
11	2	(.46 - .49 μm)	.0031141	5	.0020351	7	.0009554
12	7	(.58 - .64 μm)	.0029816	7	.0019880	5	.0009340

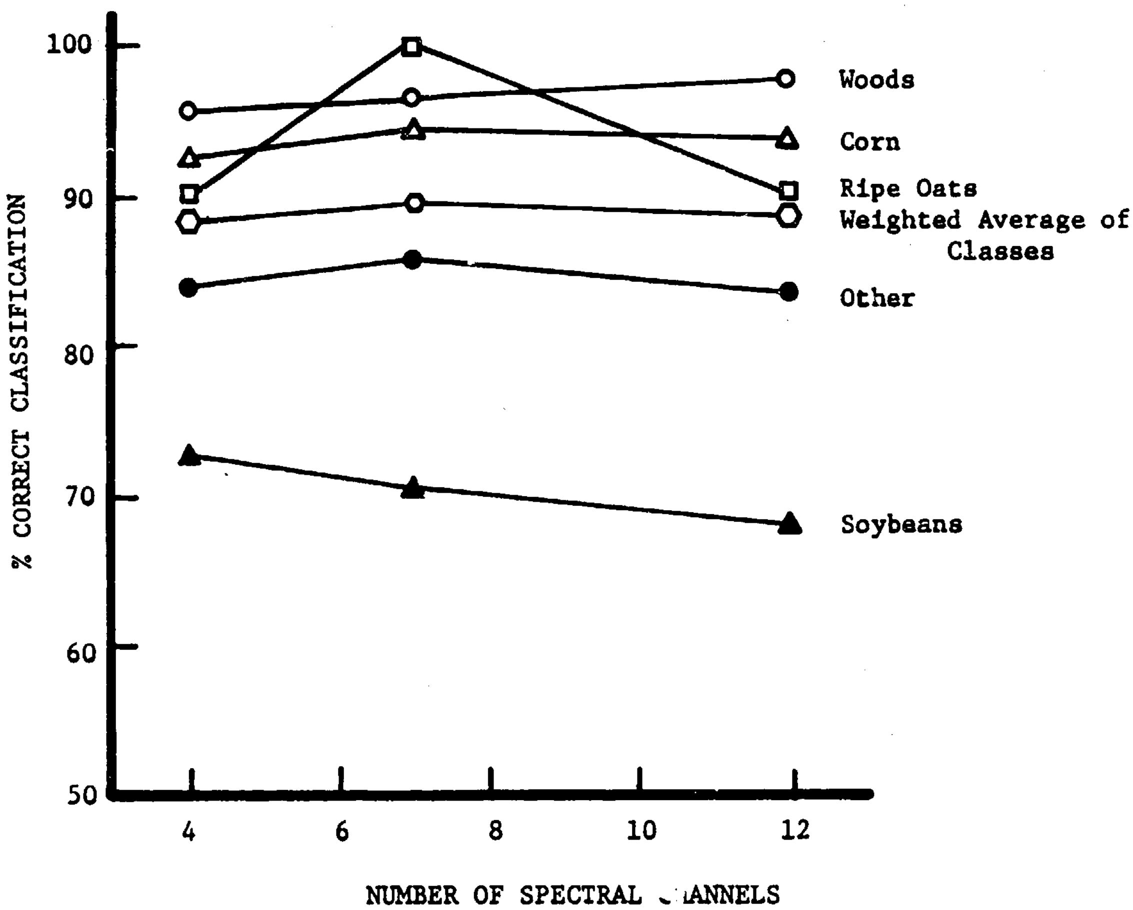


FIGURE 3-1. CLASSIFICATION ACCURACY vs NUMBER OF SPECTRAL BANDS
MICHIGAN AGRICULTURE TEST SITE

TABLE 3-2. PERFORMANCE RESULTS
MICHIGAN AGRICULTURE TEST SITE
4 Optimum Channels - 30 m Resolution

		PER CENT MISCLASSIFICATION				
SCENE CLASS (No. of Pixels)	PER CENT CORRECT CLASSIFICATION	CORN	SOY-BEANS	RIPE OATS	WOODS	OTHER
CORN (812)	92.6				0.5	6.9
SOYBEANS (284)	72.9	10.2				16.9
RIPE OATS (20)	90.0					10.0
WOODS (860)	95.2			0.1		4.7
OTHER (1168)	83.7	11.2	2.8	0.8	1.3	

Wt. Average = 88.2

TABLE 3-3. PERFORMANCE RESULTS
MICHIGAN AGRICULTURE TEST SITE
7 Optimum Channels - 30 m Resolution

SCENE CLASS (No. of Pixels)	PER CENT CORRECT CLASSIFICATION	PER CENT MISCLASSIFICATION				
		CORN	SOY-BEANS	RIPE OATS	WOODS	OTHER
CORN (812)	94.1				0.7	5.2
SOYBEANS (284)	70.4	7.8				21.8
RIPE OATS (20)	100.0					
WOODS (860)	96.4	1.9				1.7
OTHER (1168)	85.7	9.8	0.4	0.9	3.1	

Wt. Average = 89.5

TABLE 3-4. PERFORMANCE RESULTS
MICHIGAN AGRICULTURE TEST SITE
12 Optimum Channels - 30 m Resolution

SCENE CLASS (No. of Pixels)	PER CENT CORRECT CLASSIFICATION	PER CENT MISCLASSIFICATION				
		CORN	SOY-BEANS	RIPE OATS	WOODS	OTHER
CORN (812)	93.8				0.6	5.5
SOYBEANS (284)	68.0	6.3				25.7
RIPE OATS (20)	90.0					10.0
WOODS (860)	97.6	1.3				1.2
OTHER (1168)	83.3	9.7	0.4	1.1	5.3	

Wt. Average = 88.6

accuracy. This decline in classification was caused by the spectral location of the non-consensus channels and the observation condition on the data collection date. Flight logs for data collection over the Michigan Agriculture test site indicate high haze concentration on the August 5 flight. Such conditions produce scattering in the lower wavelength channels and absorption in the additional mid IR channels, and this haze may reduce classification accuracy of scenes extended beyond training sets.

The marked increase in the classification accuracy of ripe oats using the optimum 7 channels is also deceptive. The August data collection period was coincident with the harvest period for oats at the Michigan test site. As a result, few fields of unharvested ripe oats were located, and a total of only twenty pixels (at 30 meters) of this class is represented. Using 7 channel data only two additional pixels were correctly classified which had been misclassified using the 4 and 12 channel data.

There was a wide variability in the condition of soybean fields during the data collection period, resulting in generally low classification accuracy for the 12, 7, and 4 channel data. Ground information and low altitude photography indicated that this wide variation was caused by variations in planting dates and cultivation practices.

Discounting the anomalies of the ripe oat and soybean classes and the influence of these classes on average classification accuracy, the classification accuracy for the five vegetative classes tested improves little as the number of spectral bands is increased from four to seven. Since the five classes are fairly representative of the Agriculture discipline, the results indicate that adequate vegetation classification can be accomplished as well with four or five optimized channels as with twelve. The consensus channels empirically selected from Michigan agriculture data were 0.62-0.70 μm, 1.5-1.8 μm, 0.67-0.94 μm, 0.55-0.60 μm, and 9.3-11.7 μm.

As shown in Figure 3-2, these bands are located in spectral regions where the vegetation signature is most different from other signatures. Channels 6 and 8 are located in the areas of chlorophyll transmittance and absorption, at 0.55-0.60 μm and 0.62-0.70 μm respectively. Channel 9 is located in the area of high vegetative infrared reflectance near 0.8 μm; and channel 12, though not shown in the Figure 3-2 reflectance curve, is located in the thermal infrared. Channel 11, at 1.5-1.8 μm, is located in a region where the vegetation response is strongly influenced by the moisture content of the foliage.

The results of the literature survey for the Agriculture/Range/ Forestry discipline, shown in Table 3-5, provide corroboration to the spectral regions empirically selected for the Michigan test site. (The precise widths and locations of the empirically selected bands were, however, fixed prior to data collection.) Further optimization of these bands may be realized by further analysis of Figure 3-2. The 0.62-0.70 μm band is centered on a region of maximum chlorophyll A absorptance, hence measurement in this region is indicative of plant chlorophyll A content and useful in species differentiation and assessment of plant health and growth stage. Measurements in this band are most useful when the band is as near the absorptance trough as possible. It can be seen from Figure 3-2 that the lower and upper band limits of the empirically selected band encompass reflectance rises toward the yellow and near infrared spectral regions respectively. To optimize measurement in this spectral region, the bandwidth should be reduced to 0.63-0.69 μm.

The 0.67-0.94 μm band contains not only the high reflectance plateau, but also the reflectance rise between the red and infrared regions. The lower band limit should be raised to 0.75 μm to allow reflectance on the near infrared plateau where vegetative reflectance is greatest. The optimum upper band limit for this band should be at 0.95 μm to avoid measurement in the water absorptance region centered

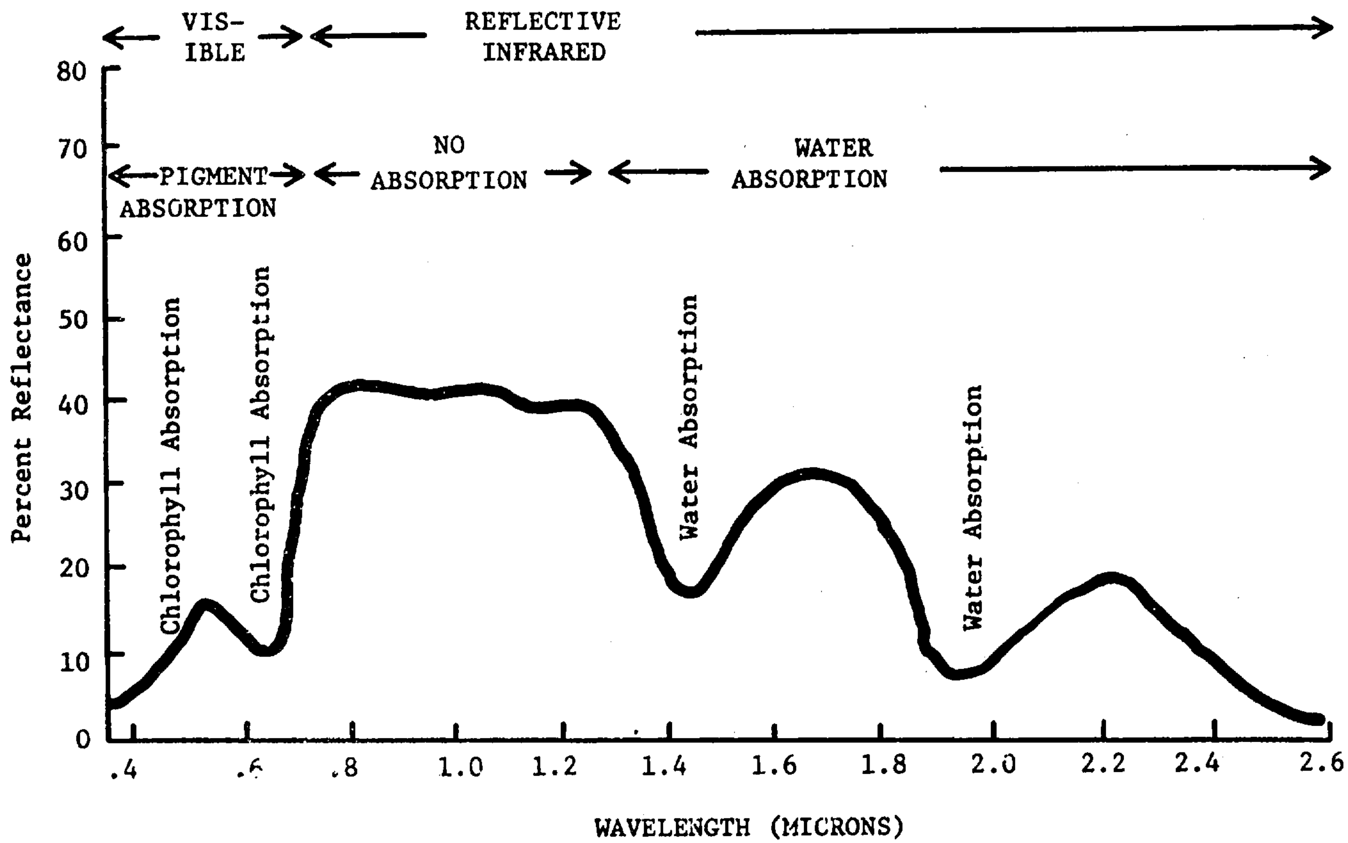


FIGURE 3-2. CHARACTERISTIC SPECTRAL REFLECTANCE CURVE OF A GREEN LEAF*

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*Laboratory for Agricultural Remote Sensing, "Remote Multispectral Sensing in Agriculture" <u>Annual Report</u> - <u>Volume 4,</u> Research Bulletin 873, December, 1970.

TABLE 3-5. LITERATURE SURVEY RESULTS - AG/RANGE/FORESTRY

SOURCE	
Theoretical Results	Allen, Grosman, Richardson - 1970
	Earing, Ginsberg - 1969
	Carnaggie - 1967
Empirical Results	Wagner, Colwell - 1972
	Sadowski, Thomson - 1972
	Nalepka, Vincent, Thomas - 1974
Systems Studies	SEOS - 1973
	EOSPDG - 1973
	Advanced Scanners and Imaging Systems - 1972

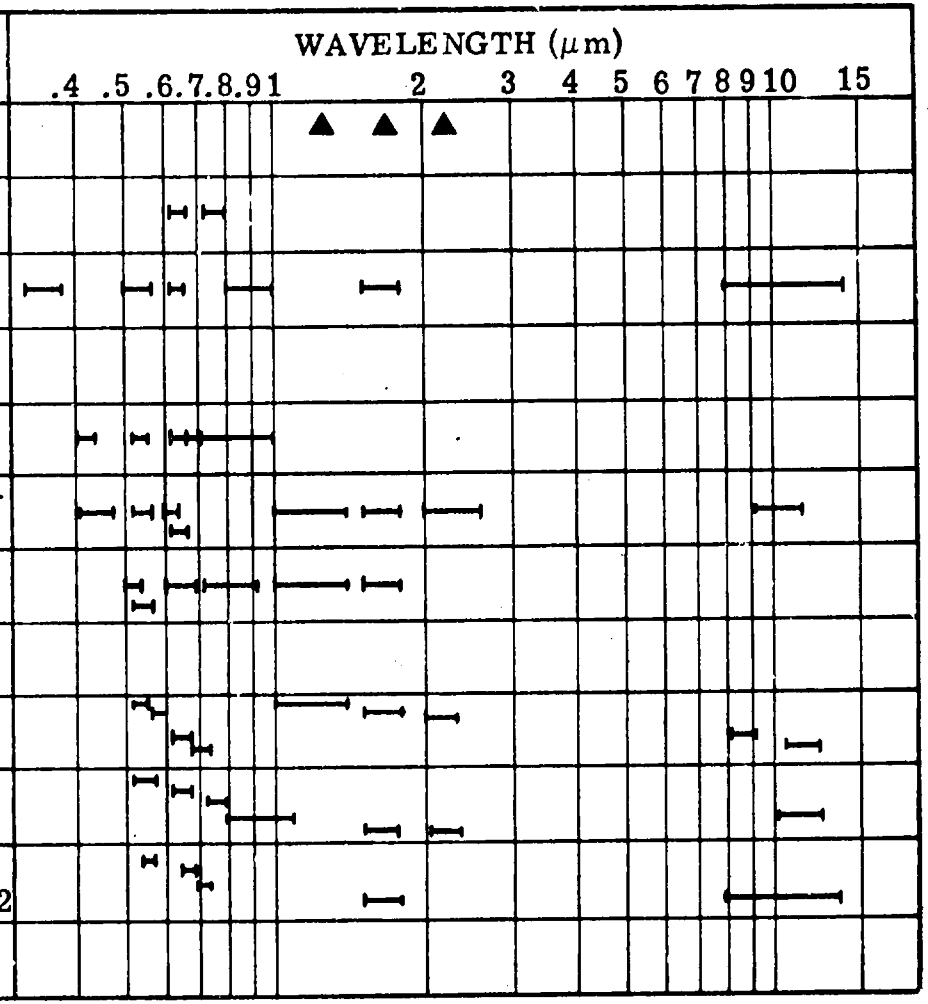

TABLE 3-5A. LITERATURE SURVEY RESULTS - AGRICULTURE/RANGE/FORESTRY OPTIMUM SPECTRAL BANDS (μm)

THEORETICAL

Allen, Gausman, Richardson

1.25
1.65
2.20
(no Δλ specified)

Earing, Ginsberg

0.62 - 0.66
0.66 - 0.72
0.72 - 0.79

Carnaggie

0.32 - 0.38
0.50 - 0.57
0.62 - 0.66
0.80 - 1.0
1.50 - 1.8
8.0 - 14.0

EMPIRICAL

Wagner, Colwell

0.40 - 0.44
0.52 - 0.55
0.62 - 0.66
0.66 - 0.72
0.72 - 0.80
0.80 - 1.0

Sadowski, Thomson

0.41 - 0.48
0.52 - 0.57
0.58 - 0.64
0.62 - 0.67
1.0 - 1.4
1.5 - 1.8
2.0 - 2.6
9.3 - 11.6

Nalepka, Vincent, Thomas

0.50 - 0.54
0.52 - 0.57
0.61 - 0.69
0.72 - 0.92
1.0 - 1.4
1.5 - 1.8

SYSTEMS STUDIES

SEOS

0.52 - 0.56
0.57 - 0.59
0.59 - 0.62
0.62 - 0.68
0.69 - 0.75
2.0 - 2.3
8.3 - 9.3
10.5 - 12.5

EOSPDG

0.52 - 0.58
0.63 - 0.68
0.74 - 0.79
0.80 - 1.0
1.55 - 1.75
2.05 - 2.35
10.3 - 12.6

Advanced Scanners and Imaging Systems

0.55 - 0.58
0.66 - 0.70
0.70 - 0.74
1.50 - 1.8
2.0 - 2.6
8.0 - 14.0

at 1.16 μm. The 0.55-0.60 μm band is an area of chlorophyll transmittance useful in assessing the growth stage and health of vegetation. As shown in Figure 3-3, peak reflectance in this region is shifted toward the 0.60 μm region with either vegetative maturity or disease infestation.

The 10.4-12.5 μm region has been the most often used and recommended thermal band. This band is selected to avoid water absorption regions on either side of the band limits and to provide broad band temperature data. Temperature has demonstrated utility in vegetative discrimination. The effects of canopy shading, evapotranspiration, and percent bare soil are often manifested as a difference in thermal radiation in vegetative scenes. The 9.3-11.7 μm band empirically selected would probably be replaced by the 10.4-12.5 μm band for satellite applications. Exact placement of a thermal band may, however, be of less importance to vegetative investigations than to other disciplines, so long as the selected thermal band provides accurate temperature measurements. The 1.5-1.8 μm band may be used as an indicator of leaf moisture content, and is thus useful in discrimination of vegetative type, growth and health. The band, however, unnecessarily overlaps into water absorption bands at each band limit, and should be narrowed to 1.55-1.75 μm.

The five bands discussed thus far are considered good for classification of vegetative species. In addition to species classification, it is desirable to assess plant health and vigor. In combination with one or more of the previous bands, spectral bands located at 0.69-0.75 μm, and 2.05-2.35 μm have been shown to be indicators of vegetative stress, insect or disease infestation, and vigor. The mid-infrared band (2.05-2.35 μm) is a further indicator of leaf moisture content. The 0.69-0.75 μm band is located on the slope between the chlorophyll absorptance band (0.63-0.69 μm) and the high reflectance near infrared band (0.75-0.95 μm). As shown in Figure 3-3, measurements

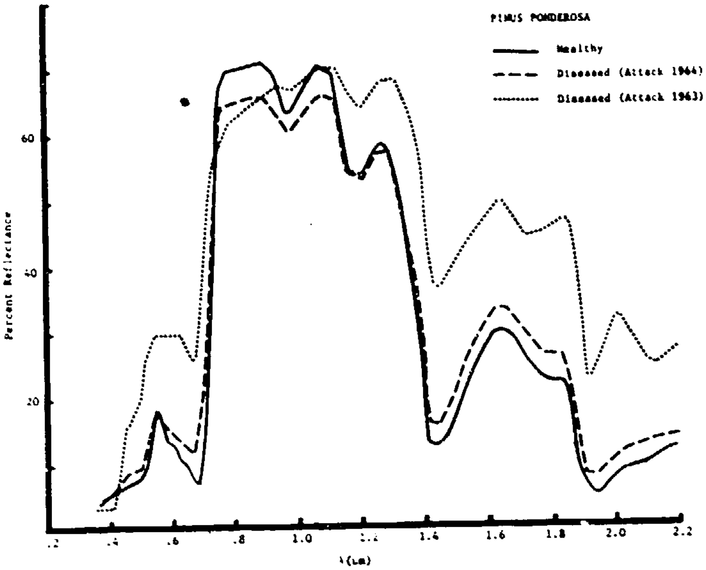

Figure 3-3a. Reflectances of Healthy and Diseased Ponderosa Pine*

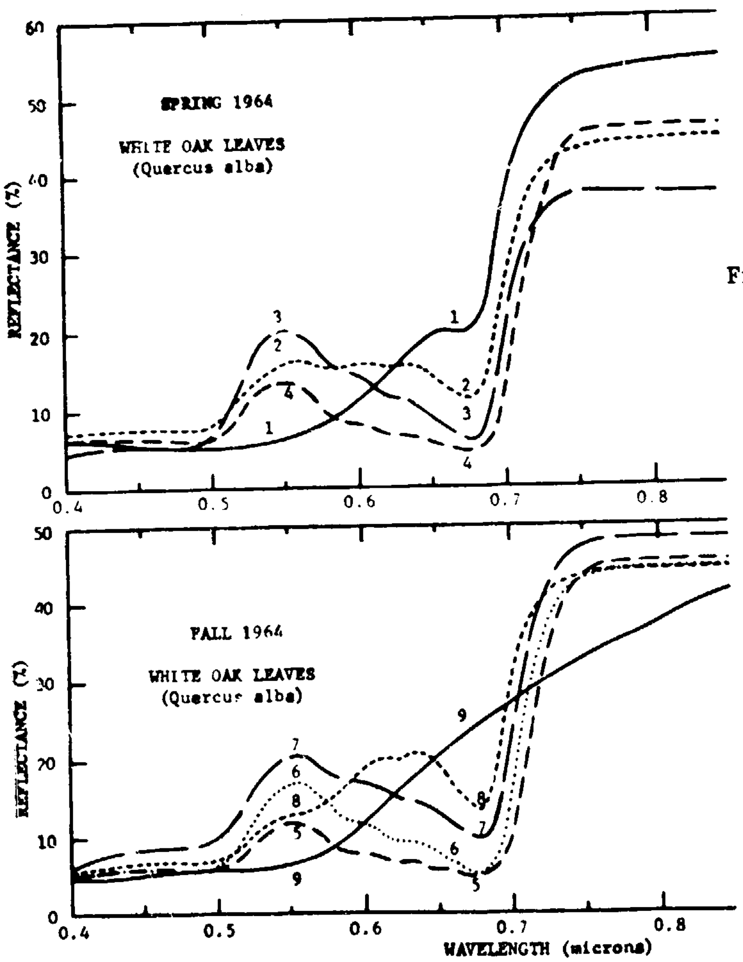

Figure 3-3b. Reflectances of White Oak Leaves*

Curve #	Date
1	April 17
2	April 22
3	May 5
4	May 18
5	Sept 18
6	Oct 21
7	Oct 26
8	Oct 28
9	Nov 2

*J. C. Schleter, V. R. Weidner and J. D. Kuder, "Spectral Properties of Naturally Occurring and Man-Made Materials," National Bureau of Standards Report 8626. December 1964

in this region may also be used as an indicator of growth stage and stress.

Prioritized recommended spectral bands for the Agriculture/Range/Forestry discipline are shown in Table 3-6. Based upon the empirical and theoretical results presented, the first five bands are considered optimum for classifying vegetative scenes. The remaining two bands are added to assess vegetative health and vigor. The 2.05-2.35 μm band is included in Table 3-6 as an option to the 1.55-1.75 μm band.

3.3 URBAN LAND USE

The bands shown in Table 3-7 were selected from the Baltimore Land Use data for the simulated 30 m resolution case. Bands 8, 9, and 12 ranked high as vegetative discriminators; channel 10 was used primarily for detection of water; and channels 1, 4, and 11 were found to be good for the discrimination of impervious materials. Tables 3-8 through 3-13 present detailed performance results of Levels I, II, and III land use classification using the best 4, 7, and 12 spectral channels. Table 3-14 summarizes the percentage correct classification of Tables 3-8 through 3-13. Analysis of the Table 3-14 results indicates that none of the individual Urban Land Use classes showed a marked increase classification accuracy as the number of spectral bands was increased from 4 to 12.

The weighted average results of Levels I, II, and III Urban Land Use classification accuracies using 12, 7, and 4 channel data are detailed in Table 3-15 and shown graphically in Figure 3-4. As in the agriculture case, there is little improvement in the classification accuracy for Levels I and II, or III as the number of channels is increased. Empirically then, four channels appear to be adequate for Levels I, II, and III, Urban Land Use classification.

Insufficient literature dedicated to assessment of optimum bands was found for Urban Land Use investigations. In view of this, the

TABLE 3-6. RECOMMENDED OPTIMUM BANDS
AGRICULTURE/RANGE/FORESTRY
(PRIORITIZED)

AGRICULTURE/RANGE/FORESTRY
0.63 - 0.69 μm
0.75 - 0.95 μm
10.4 - 12.5 μm
0.55 - 0.60 μm
*1.55 - 1.75 μm
2.05 - 2.35 μm
0.69 - 0.75 μm

* or 2.05 - 2.35 μm

TABLE 3-7. CHANNEL ORDERING AND PROBABILITY OF MISCLASSIFICATION FOR 4 x 4 SMOOTHED BALTIMORE AIRCRAFT DATA (28.8 m RESOLUTION)

(CLASSES SHOWN IN TABLE 3-9)

CHANNEL	PROBABILITY OF MISCLASSIFICATION
10 (1.0 - 1.4 μm)	.0473
1 (0.41 - 0.48 μm)	.0080
12 (9.3 - 11.7 μm)	.0035
9 (0.67 - 0.94 μm)	.0019
8 (0.62 - 0.70 μm)	.0011
4 (0.50 - 0.54 μm)	.0007
11 (2.0 - 2.6 μm)	.0006
2 (0.46 - 0.49 μm)	.0005
7 (0.58 - 0.64 μm)	.0004
3 (0.48 - 0.52 μm)	.0004
5 (0.52 - 0.57 μm)	.0004
6 (0.55 - 0.60 μm)	.0004

TABLE 3-8: PERFORMANCE MATRICES

LEVEL I LAND USE* 4 Channels

AGGREGATED COMPUTER SPECTRAL CLASSES

GROUND TRUTH	URBAN	AG	FOREST	WATER	UNCLAS.
URBAN (1)	85.9	7.9	1.3		5.1
AGRICULTURE (2)	14.3	69.1	4.8		11.9
FOREST (4)	14.8		88.2		3.0
WATER (5)				70.0	30.0

LEVEL II LAND USE*

AGGREGATED COMPUTER SPECTRAL CLASSES

GROUND TRUTH	RES	COM/IND	AG	PAST	FOR	WATER	UNCLAS.
RESIDENTIAL (11)	63.1	23.6	7.7	0.1	1.9		3.2
COMMERCIAL/ INDUSTRIAL (12/13)	26.5	58.2	4.1	3.1			8.2
CROPLAND (21)	13.3		46.7	13.3	6.7		20.0
PASTURE (22)	14.8		11.1	61.8	3.7		7.4
FOREST Deciduous (41)	8.8				88.2		3.0
WATER (50)						70.0	30.0

*ANDERSON LAND USE CLASSES ARE SHOWN IN PARENTHESES

TABLE 3-9. PERFORMANCE MATRIX

BALTIMORE, MARYLAND

LEVEL III COMPUTER SPECTRAL CLASSIFICATION OF LAND USE* 4 Channels

GROUND TRUTH	Number of Points	FAM Single Family Res. (111)	APT1 APT2 Multiple Family (112)	RLR SOIL ASPH Commercial (121/122)	MDR DR Industrial (130)	SOIL CROP Cropland (210)	PASTURE Pasture (220)	FOREST Deciduous Forest (410)	Water (500)	Unclassified
Single Family Residential (111)		62.7	16.0	1.3	2.7	10.7		4.0		2.7
Multi-family (112) and Institutional (160)		15.9	32.7	12.2	29.3	4.9	1.2			3.7
Commercial (121/122)		11.8	19.7	33.3	25.5	2.0	3.9			3.9
Industrial (13)		4.3	17.0	42.5	14.9	6.4	2.1			12.8
Cropland (210)		6.7	6.7			46.7	13.3	6.7		20.0
Pasture (220)		7.4	7.4			11.1	61.8	3.7		7.4
Deciduous Forest (410)		8.8						88.2		3.0
Water (500)									70.0	30.0

*State of Maryland Land Use Classes are shown in parentheses

TABLE 3-10. PERFORMANCE MATRICES

LEVEL I LAND USE* 7 Channels

GROUND TRUTH	AGGREGATED COMPUTER SPECTRAL CLASSES: URBAN	AG	FOREST	WATER	UNCLAS.
URBAN (1)	83.9	6.3	1.2		2.0
AGRICULTURE (2)	14.3	71.4	7.2		7.2
FOREST (4)	5.9		94.1		
WATER (5)				12.5	87.5

LEVEL II LAND USE* 7 Channels

GROUND TRUTH	AGGREGATED COMPUTER SPECTRAL CLASSES: RES	COM/ IND	AG	PAST	FOR	WATER	UNCLAS.
RESIDENTIAL (11)	66.3	21.7	6.4	0.6	1.9		3.2
COMMERCIAL/ INDUSTRIAL (12/13)	25.5	52.0	4.1	1.0			17.4
CROPLAND (21)	6.7	6.7	60.0	6.7	6.7		13.3
PASTURE (22)	11.1	[illegible]	14.8	59.3	7.3		3.7
FOREST Deciduous (41)					94.1		
WATER (50)						100	

*ANDERSON LAND USE CLASSES ARE SHOWN IN PARENTHESES

TABLE 3-11. PERFORMANCE MATRIX

BALTIMORE, MARYLAND

LEVEL III COMPUTER SPECTRAL CLASSIFICATION OF LAND USE* 7 Channels

		FAM	APT1 APT2	RLR SOIL ASPH	MDR DR	SOIL CROP	PASTURE	FOREST		
GROUND TRUTH	Number of Points	Single Family Res. (111)	Multiple Family (112)	Commercial (121/122)	Industrial (130)	Cropland (210)	Pasture (220)	Deciduous Forest (410)	Water (500)	Unclassified
Single Family Residential (111)		62.7	16.0		2.7	9.3	1.3	4.0		4.0
Multi-family (112) and Institutional (160)		13.4	41.5	13.4	25.6	3.6				2.4
Commercial (121/122)		11.8	15.7	29.4	31.4	2.0	2.0			7.9
Industrial (13)		6.4	17.0	19.2	23.4	6.4				27.7
Cropland (210)		6.7	6.7			60.0	6.7	6.7		13.3
Pasture (220)		5.9	3.0			11.8	47.1	5.9		3.0
Deciduous Forest (410)		3.0	3.0					94.1		
Water (500)									12.5	87.5

*State of Maryland Land Use Classes are shown in parentheses.

TABLE 3-12. PERFORMANCE MATRICES

LEVEL I LAND USE* 12 Channels

GROUND TRUTH	AGGREGATED COMPUTER SPECTRAL CLASSES: URBAN	AG	FOREST	WATER	UNCLAS.
URBAN (1)	85.9	7.1	0.8		6.3
AGRICULTURE (2)	11.9	73.8	7.2		7.2
FOREST (4)	8.9	3.0	88.2		
WATER (5)	2.5			20.0	77.5

LEVEL II LAND USE* 12 Channels

GROUND TRUTH	AGGREGATED COMPUTER SPECTRAL CLASSES: RES	COM/IND	AG	PAST	FOR	WATER	UNCLAS.
RESIDENTIAL (11)	64.3	23.6	8.3	1.3	1.3		1.3
COMMERCIAL/ INDUSTRIAL (12/13)	34.7	48.0	2.0	1.0			14.3
CROPLAND (21)	13.3		53.3	13.3	6.7		13.3
PASTURE (22)	11.1		14.8	63.0	7.4		3.7
FOREST Deciduous (41)	8.9			3.0	88.2		
WATER (50)	2.5					20.0	77.5

*ANDERSON LAND USE CLASSES ARE SHOWN IN PARENTHESES

TABLE 3-13. PERFORMANCE MATRIX

BALTIMORE, MARYLAND

LEVEL III COMPUTER SPECTRAL CLASSIFICATION OF LAND USE * 12 Channels

		FAM	APT1 / APT2	BLR / SOIL / ASPH	MDR / DR	SOIL / CROP	PASTURE	FOREST		
GROUND TRUTH	Number of Points	Single Family Res. (111)	Multiple Family (112)	Commercial (121/122)	Industrial (130)	Cropland (210)	Pasture (220)	Deciduous Forest (410)	Water (500)	Unclassified
Single Family Residential (111)		58.7	17.3	4.0		12.0	2.7	2.7		
Multi-family (112) and Institutional (160)		14.6	39.0	13.4	25.6	4.8				2.4
Commercial (121/122)		9.8	23.6	31.4	25.5	2.0	2.0			5.9
Industrial (13)		10.6	25.5	21.3	17.0	2.1				23.4
Cropland (210)		6.7	6.7			53.3	13.3	6.7		13.3
Pasture (220)		11.1				14.8	63.0	7.4		3.7
Deciduous Forest (410)		5.9	3.0				3.0	88.2		
Water (500)		2.5							20	77.5

*State of Maryland Land Use Classes are shown in parentheses

TABLE 3-14. PROBABILITY OF CORRECT CLASSIFICATION

FOR VARIOUS NUMBERS OF CHANNELS

Baltimore Land Use Test Site

ANDERSON LEVEL I

Classification \ # of Channels	4	7	12
Urban (1)	85.9	83.9	85.9
Agriculture (2)	69.1	71.4	72.8
Forest (4)	88.2	94.1	88.2
Water (5)	100	100	100

ANDERSON LEVEL II

Classification \ # of Channels	4	7	12
Residential (11)	63.1	66.3	64.3
Commercial/ Industrial (12/13)	58.2	52.0	48.0
Cropland (21)	46.7	60.0	53.3
Pasture (22)	61.8	59.3	63.0
Forest (41)	88.2	94.1	88.2
Water (50)	100	100	100

MARYLAND LEVEL III

Classification \ # of Channels	4	7	12
Single Family Residential (111)	62.7	62.7	58.7
Multi-family (112) and Institutional (160)	32.7	41.5	39.0
Commercial (121/122)	33.3	29.4	31.4
Industrial (130)	14.9	23.4	17.0
Cropland (210)	46.7	60.0	53.3
Pasture (220)	61.8	47.1	63.3
Deciduous Forest (410)	55.2	94.1	88.2
Water (500)	100	100	100

TABLE 3-15. PERFORMANCE MATRICES

BALTIMORE, MARYLAND - AVERAGE ACCURACY

4 Channels	% CORRECT	% ERRORS	
		Commission	Omission
LEVEL I	85.7	9.2	5.1
LEVEL II	67.4	27.5	5.1
LEVEL III	51.8	42.5	5.1

7 Channels	% CORRECT	% ERRORS	
		Commission	Omission
LEVEL I	85.2	8.1	6.7
LEVEL II	67.9	25.4	6.7
LEVEL III	54.9	38.4	6.7

12 Channels	% CORRECT	% ERRORS	
		Commission	Omission
LEVEL I	86.3	8.6	5.1
LEVEL II	65.5	29.8	5.1
LEVEL III	52.6	42.3	5.1

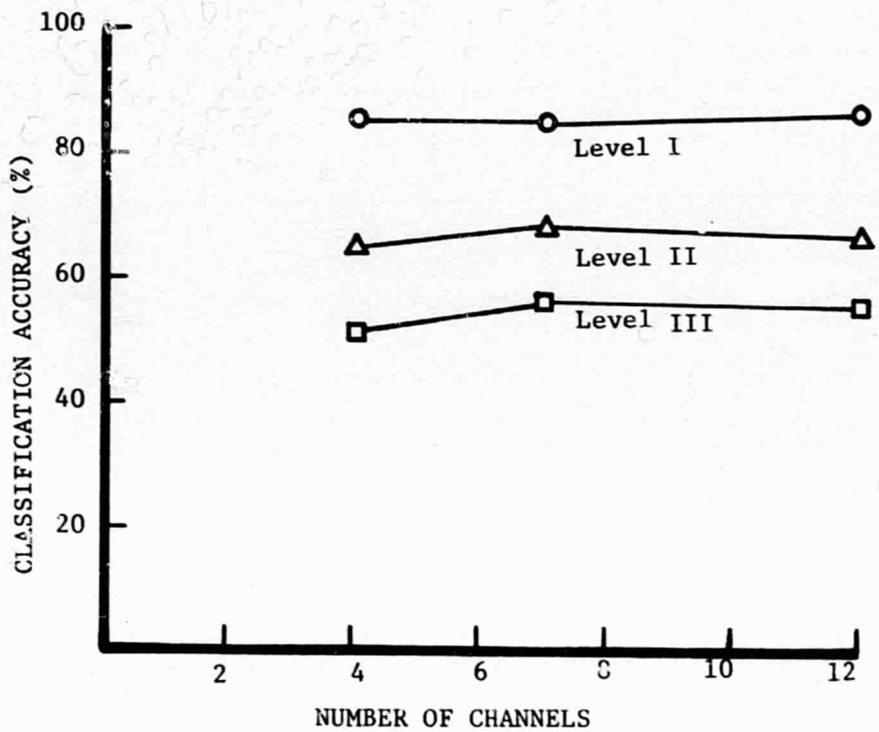

FIGURE 3-4. BALTIMORE LAND USE CLASSIFICATION
EFFECTS OF NUMBER OF CHANNELS

28.8 m Data, 5/15/72 - 1345 Hrs.

Urban Land Use results are based primarily upon the Baltimore data results presented in this study and an analysis of laboratory reflectance data on materials to be encountered in Land Use scenes.

With the exception of channel 10, the channels selected for the land use study were generally in the spectral regions predicted theoretically. Band 10 was ranked unusually high as a result of its use as a land/water boundary identifier. A more appropriate band for land/water interface delineation in urban land use studies (not available in the Baltimore data) would be an 0.8-1.1 μm band. This band would aid in vegetative discrimination in addition to delineating land/water interfaces and would replace both channels 9 and 10 shown in Table 3-7. The 0.62-0.70 μm and the 9.3-11.7 μm bands would be modified to 0.63-0.69 μm and 10.4-12.4 μm, respectively, as described in the Agriculture/Range/Forestry study. The remainder of the top seven bands in Table 3-7 would remain unchanged.

The anticipated task for Urban Land Use is to classify urban areas at least to the Anderson Level II categories. To accomplish this, selected bands will be required to classify various types of pervious and impervious materials, differentiate between vegetative types, and delineate land/water boundaries. The 10.4-12.5 μm band would be the most useful band for urban land use classification, provided that data are collected near noon, when maximum temperature contrast between man-made and natural categories occurs. Temperature has been found to be an indicator of the concentration of man's activities and has also been useful in vegetation discrimination for land use applications. The 10.4-12.5 μm band would probably not be as useful if data were collected at 0930 hours. The 0.63-0.69 μm band is primarily a vegetation band as described in the Agriculture/Range/Forestry portion of the study. The 0.50-0.54 μm, 2.0-2.6 μm, and 0.42-0.48 μm bands are pervious/impervious materials and vegetation discriminators. Though ranked ninth empirically, the 0.58-0.64 μm is

deemed necessary to land use classification because of its utility in radiation balance and albedo measurements. Recommended spectral bands for the Urban Land Use discipline are shown in Table 3-16.

3.4 GEOLOGY AND SOILS

The geological classification task undertaken was lithological or mineral soil classification. As opposed to the delineation of structure which may be done with color imagery or black and white single channel imagery collected under suitable conditions, a diversity of spectral bands may be required for successful lithologic classification. Twenty-one materials were identified in the White Sands data. These classes appear in Table 3-17.

Data from the White Sands Geology test site were evaluated first to determine the optimum ratios from the training data. Ratios were selected as input features because of previous experience indicating that spectral shape information was more useful than the spectral reflectance information in delineating certain lithologic units such as different silicates and iron-bearing formations. Generation of the optimum ratios, shown in Table 3-18, was accomplished by evaluating 121 individual target areas representing 21 different classes of materials to be recognized. Spectral bands comprising these ratios were then prioritized. These prioritized spectral band results appear in Table 3-19. The prioritization represented in Tables 3-18 and 3-19 are attempts to minimize the overall probability of misclassification for all scene classes. The prioritization did not maximize the probability of detecting a particular material of economic or geological inferential importance. As may be seen in the analysis of data test sets, the addition of bands directed towards identifying particular materials does increase the probability of identifying that material.

For the White Sands Geology test site, the twenty one separate scene materials were classified using 15, 7, and 5 spectral channels.

TABLE 3-16. RECOMMENDED OPTIMUM BANDS URBAN LAND USE (PRIORITIZED)

URBAN LAND USE
10.4 - 12.5 μm
0.8 - 1.1 μm
0.63 - 0.69 μm
0.50 - 0.54 μm
2.0 - 2.6 μm
0.42 - 0.48 μm
0.58 - 0.64 μm

TABLE 3-17

WHITE SANDS GEOLOGY TEST SITE

Scene Classes to be Recognized

Scene Class	Name	Description
1	Gypsum sand near alkali flat	white deposits associated alkali flat, partially gypsum sand, may include some quartz sand
2	Soil (recent?)	a background soil type cut by youngest drainage deposits
3	Red alkali deposit	distinct red deposit north of the white sands
4	Soil (dissected)	a distinct soil type considered younger than target 2 and of different composition or cover
5	Dark drainage soil (most recent?)	appears very dark in natural color photography, may be some vegetative cover
6	Red alkali deposit	broad region of alkali flats orange-red to red-brown sediment materials
7	Alluvial fan - geologic map shows Qal	fan on eastern San Andres at mouth of Grapevine Canyon and some remnant sediment on the pediment
8	Soil	second background soil type
9	Pediment - Paleo-alluvial fan	appears to be the remaining exposed foot of a previous period of alluvium, probably with associated soil remnants on the pediment
10	Soil (erosional remnant)	remnants of a pediment soil highly dissected and appearing dark greenish-gray
11	Precambrian crystallines	granite chiefly. Other core exposures of metamorphics are not specifically known, but may be omitted from this class and hopefully will class with some of the more mafic rich soils

TABLE 3-17 (cont.)

12	Dolomite	several Ordovician and a Silurian dolomite stratigraphically contiguous. An Ordovician basal sandstone is also included here, but considered of insignificant thickness. It may interfere with the boundary between crystallines and dolomites
13	Limestone and calcareous sediments	Devonian through Upper Pennsylvanian calcareous sediments of mixed description. Statistical stratification failed to separate limestone from mixtures of silts and sands with carbonaceous shale.
14	Abo Redbeds	dark reddish-brown shales and siltstone, some grey and red also
15	Yeso and San Andres Formations	iron stained sandstone and calcareous sediments
16	Slope material	general valley fill material not recognizable as rock outcrop and likely to have mixtures of rock types, highly weathered, with partial soil development and/or cover
17	Multi-colored drainage soil	a unique soil type of extremely mottled appearance in the red seen to dissect most soil classes
18	Lake Lucero	playa lake deposits
19	Gypsum sand	
20	Bolson sediment	dark material seen to underlie or be in close proximity to the gypsum sand deposits
21	Darkest bolson deposits	similar situation to target 22, but spectrally distinctive.

TABLE 3-18. PRIORITIZED RATIOS
GEOLOGY TEST SITE

Ranking	Ratio	Probability of Misclassification
1	0.71-0.75 / 0.46-0.50	.14870
2	1.18-1.30 / 0.71-0.75	.06174
3	0.57-0.63 / 0.40-0.44	.03793
4	0.64-0.68 / 0.53-0.57	.02822
5	2.10-2.36 / 0.82-0.87	.02181
6	0.97-1.05 / 0.76-0.80	.01839
7	0.46-0.50 / 0.34-0.40	.01574
8	9.30-9.80 / 8.30-8.80	.01365
9	2.10-2.36 / 0.64-0.68	.01242
10	0.97-1.05 / 0.64-0.68	.01107
11	0.82-0.87 / 0.53-0.57	.01055
12	2.10-2.36 / 1.05-1.09	.01011
13	0.46-0.50 / 0.40-0.44	.00970

TABLE 3-19. PRIORITIZED SPECTRAL BANDS
WHITE SANDS GEOLOGY TEST SITE

Ranking	Spectral Band
1	0.71 - 0.75
2	0.46 - 0.50
3	1.18 - 1.30
4	0.57 - 0.63
5	0.40 - 0.44
6	0.64 - 0.68
7	0.53 - 0.57
8	2.10 - 2.36
9	0.82 - 0.87
10	0.97 - 1.05
11	0.76 - 0.80
12	0.34 - 0.40
13	9.30 - 9.80
14	8.30 - 8.80
15	1.05 - 1.09

The classification results are given in Tables 3-20, 3-21, and 3-22. As can be seen in Figure 3-5, a marked improvement in average classification accuracy was realized as the number of spectral channels was increased from 5 to 15. However, some scene classes (3, 15, 18, 20, and 21) show little decrease in classification accuracy as the number of spectral channels is reduced to five. Table 3-23 is a useful summary of this data.

This dependence of classification accuracy upon the number of spectral bands follows from the relatively large number of scene materials to be classified. This large number of classes, however, is representative of the variety of the geology and soils found in arid regions such as New Mexico, and thus the number of bands may be indicative of the spectral requirements.

The soils and sediments are well identified by the first four bands of Table 3-19. A marked improvement in classification is noted for class 10, a probably ferrous iron containing soil identified with the aid of the 0.46-0.50 μm/0.34-0.40 μm ratio brought in the 7 ratio data. Class 1, gypsum and quartz sand, and class 11, granite, are identified by the silicate reststrahlen registered by channels 9.3-9.8 μm and 8.3-8.8 μm. Class 12 and 13 are carbonates identified best by channels 1.1-1.35 μm and 2.0-2.35 μm both available only in the 15 channel classification. Class 6 contains limonite and goethite ferric oxides and class 14 contains thematite, another ferric oxide. Improvements in classification (5 optimum versus 7 optimum spectral channels) are based on the availability of the ratio 0.64-0.68 μm/0.53-0.57 μm in the 7 channel data. The improvement classification in the 15 channel data is due to the availability of the ratio 0.97-1.05 μm/0.64-0.68 μm. Both these ratios delineate ferric iron containing materials from other scene materials. This leads to the empirical results for the identification of quartz (silicates), ferrous and ferric (iron oxides), and carbonates given in Table 3-24.

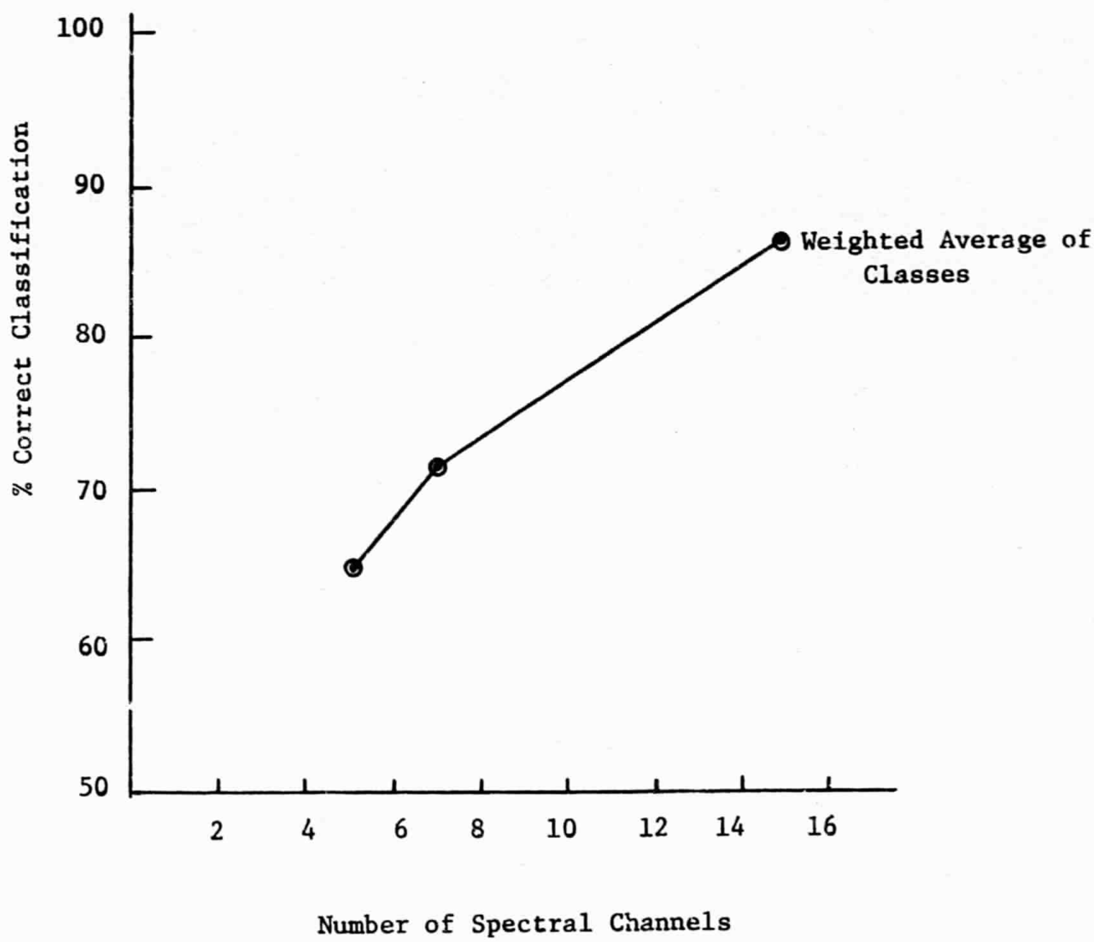

FIGURE 3-5. CLASSIFICATION ACCURACY vs NUMBER OF SPECTRAL BANDS
WHITE SANDS GEOLOGY TEST SITE

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TABLE 3-20. PERFORMANCE MATRIX - WHITE SANDS GEOLOGY TEST SITE
3 OPTIMUM RATIOS, 4 OPTIMUM CHANNELS

TRAINING SET NUMBER (SEE TABLE 3-17)

SCENE CLASS	% CLASS	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	% UN CLASS.
1	63.0		5.5	22.0	2.6	0.1	6.0	0.1									0.7						
2	56.4	25.4		4.0	13.3	0.4			0.1								0.4						
3	92.6	7.4																					
4	75.7	3.2	11.9	0.8		4.8	2.5	0.4									0.7						
5	75.8		0.3	0.3	6.3		0.8	4.3	3.5	1.5	3.8						3.5						
6	79.2				2.7			12.8									5.4						
7	21.5				2.5	2.2	2.2			4.8	1.2		0.2			4.6	63.1						
8	80.0										17.5												
9	34.3						7.1	10.7			5.7		0.7				41.4						
10	67.1				1.4	8.6			14.3	5.7							2.9						
11	2.6		1.4		1.7	5.0	1.8	2.9	0.4	1.6	2.4		12.2	10.5	17.4	17.4	17.0						3.7
12	20.4		0.2	0.1		0.1	0.2			0.2	0.2	2.7		12.4	18.9	32.2	11.7						
13	65.8					0.2	0.1	0.4		0.2	0.8	0.3	6.4		9.8	2.2	13.9						
14	75.9						0.2					0.9	4.6	4.9		4.9	8.5						
15	69.4							0.1		0.8		3.6	3.2	3.9	2.0		16.9						
16	59.9				0.1	0.4	0.1	2.5		6.0	1.0	1.5	1.6	5.4	3.2	18.4							0.1
17	83.2																			0.4	9.0		7.4
18	92.7																			3.7		3.6	
19	81.7																		12.9		0.1	5.3	
20	96.4																	3.6					
21	95.5																		3.4	1.1			

WEIGHTED AVERAGE ACCURACY OF CLASSIFICATION - 66.4%

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TABLE 3-21. PERFORMANCE MATRIX - WHITE SANDS GEOLOGY TEST SITE
4 OPTIMUM RATIOS, 7 OPTIMUM CHANNELS

TRAINING SET NUMBER (SEE TABLE 3-17)

SCENE CLASS	% CLASS	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	% UN CLASS.
1	75.3		8.4	11.0	3.4																		0.2
2	58.9	27.1		0.1	13.0																		
3	94.0	5.7	0.3																				
4	72.2	[illegible].6	15.0			6.8	0.9	0.7									0.7						0.1
5	79.3		0.5		17.8			1.0	5.0	2.3	1.0						3.0						
6	79.2							14.0				1.3					5.4						
7	38.0					0.5	2.4			5.3	1.5	8.2	0.5			10.7	32.9						
8	90.0									5.0	5.0												
9	37.1					3.6		12.9			7.1	2.9					36.4						
10	84.3					1.4		1.4	8.6	4.4													
11	14.5		0.1		0.5	3.7	1.1	3.4	0.3	0.9	2.8		16.6	9.5	6.9	21.5	14.9						3.5
12	26.5		0.1					0.2	0.1	0.1	0.1	5.5		17.2	3.5	30.4	15.4				0.1		0.7
13	69.0							0.4		0.3	0.4	1.9	8.4		0.3	9.2	10.7						0.2
14	86.1	0.6											0.4	2.8		1.3	8.7						
15	69.9							0.5		0.4		3.1	5.5	3.0	0.7		17.2						
16	65.5					0.1	0.3	3.0		5.0	0.8	2.2	2.7	4.7	7.6	12.7							0.1
17	84.[illegible]																			0.1	12.8		2.7
18	93.[illegible]																			3.9		2.7	
19	80.6																		11.2		0.1	8.1	
20	96.4																	3.6					
21	96.6																		2.3	1.1			

WEIGHTED AVERAGE ACCURACY OF CLASSIFICATION - 66.8%

TABLE 3-22. PERFORMANCE MATRIX - WHITE SANDS GEOLOGY TEST SITE
13 OPTIMUM RATIOS, 15 OPTIMUM CHANNELS
TRAINING SET NUMBER (SEE TABLE 3-17)

SCENE CLASS	% CLASS	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	% UN CLASS.
1	90.4		4.3		0.2												1.7						3.4
2	77.5	10.4			11.5	0.2						0.1					0.3						
3	99.7		0.3																				
4	80.4	0.3	8.9			4.0			0.1			0.1					0.2						
5	83.4		1.8		10.8				0.8	0.8							1.5						1.0
6	96.6							2.7		0.7													
7	80.6						0.7			2.9	1.0	3.4	1.7	1.5		5.1	3.2						
8	100.0																						
9	85.0							3.6			0.7		1.4		0.7	0.7	7.9						
10	95.7							1.4		2.9													
11	43.7									0.1			19.1	10.9	7.1	4.7	2.6						11.8
12	57.7							0.6		0.1		6.6		10.7	5.1	9.4	4.0						5.1
13	73.7							1.3		0.1		2.8	8.9		2.5	1.7	2.7						6.2
14	96.1											0.2	0.8	0.3		0.5	2.1						0.2
15	72.6							1.4				3.0	9.2	0.7	1.1		11.1						0.7
16	79.8							0.4		2.8		0.4	0.4	1.3	4.9	9.0							1.0
17	94.2																				3.9		1.9
18	99.0																						1.0
19	98.2																		0.6		0.1		1.2
20	96.8																	3.2					
21	98.9																		1.1				

WEIGHTED AVERAGE ACCURACY OF CLASSIFICATION - 81.5%

TABLE 3-23. PROBABILITY OF CORRECT CLASSIFICATION FOR 5, 7, and 15 CHANNELS

GEOLOGY

CLASS/#CLASSES	5	7	15
1	63.0	75.3	90.4
2	56.4	58.9	77.5
3	92.6	94.0	99.7
4	75.7	73.3	86.4
5	75.8	74.3	83.4
6	79.2	79.2	96.6
7	20.5	38.0	50.0
8	80.0	90.0	100.0
9	34.3	37.1	85.0
10	67.1	84.3	95.7
11	2.6	14.9	43.7
12	20.4	36.5	57.7
13	65.8	69.0	73.7
14	75.9	86.1	96.1
15	69.9	61.9	72.6
16	59.9	65.8	79.6
17	83.2	84.3	74.2
18	93.7	93.4	99.0
19	81.7	80.6	98.2
20	96.4	96.4	96.8
21	95.4	96.6	98.9

TABLE 3-24. BANDS FOR MINERAL IDENTIFICATION

MINERAL	SPECTRAL BANDS (Micrometers)
Silicate	9.3 - 9.8, 8.3 - 8.8
Ferric	0.64 - 0.68, 0.53 - 0.57, 0.91 - 1.05
Ferrous	0.46 - 0.50
Carbonates	1.1 - 1.35, 2.0 - 2.35

In the geology discipline, the assumed objective was the classification of soils and mineral resources. Theoretical and other empirical studies support the spectral channel ordering results. The results from the theoretical and empirical studies review, Table 3-25, and their band selection Table 3-25A are discussed below. The 8.3-9.3 μm and 10.4-12.5 μm thermal bands in the silicate reststrahlen region have been shown to be effective in the differentiation of silicates from other rock types and of differentiation between various silicate types. Measurements in the 0.63-0.69 μm region provide albedo information necessary to assess thermal inertia and heat capacity of various rock types. This band, combined with a band in the mid-infrared region is also effective in detecting the presence of vegetative cover (such as lichen or grass) on geologic materials. The 0.52-0.56 μm band, in combination with the 0.63-0.69 μm band is an indicator of the presence of iron oxide, and hence, ferric iron. The 2.05-2.35 μm band may indicate the presence of hydroxyl ions in surface materials and thus can be used to differentiate soil types and metamorphic and other rock types.

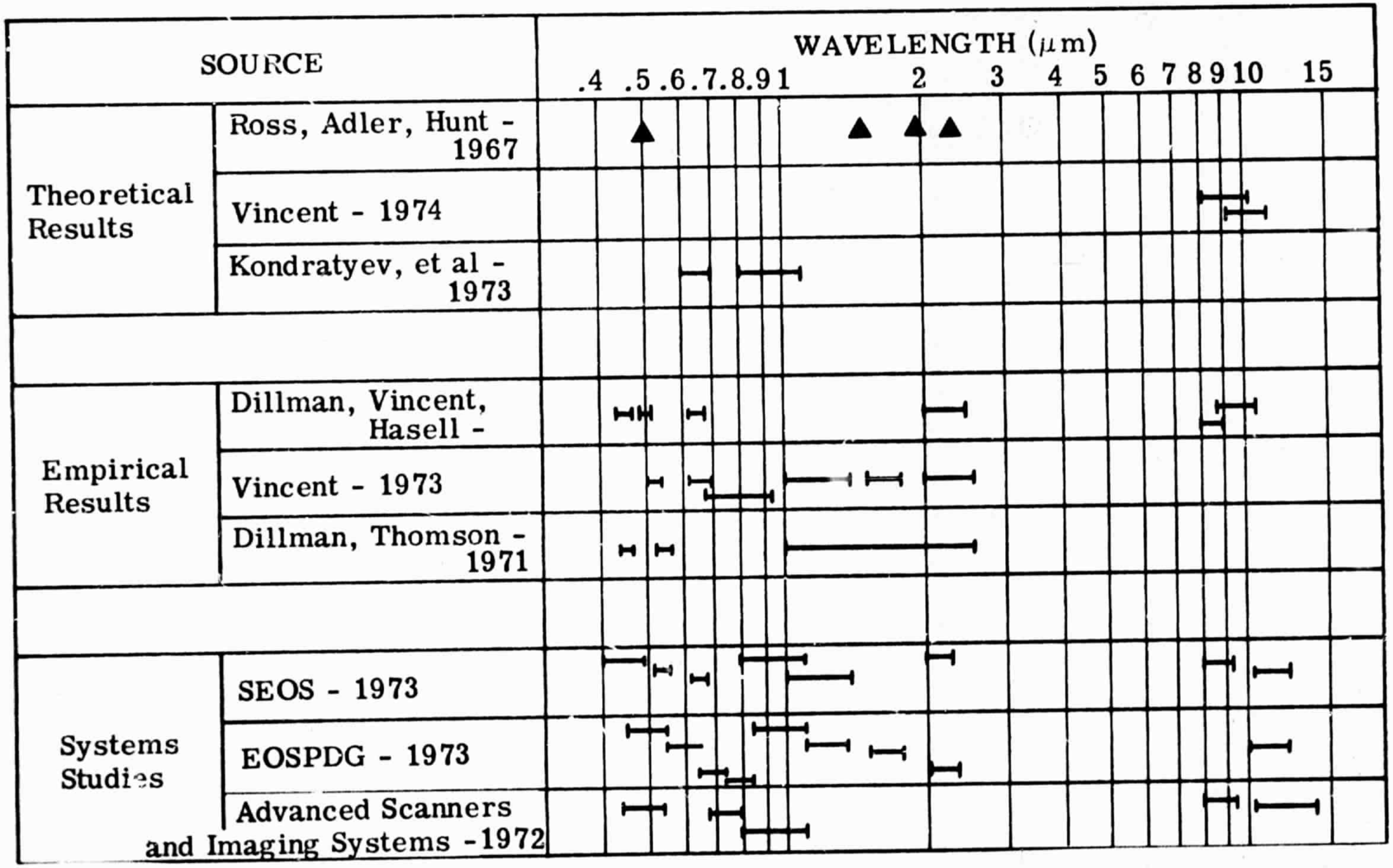
The 1.1-1.35 μm band is also useful for carbonate identification. The 1.55-1.75 μm band is potentially useful in the detection of bauxite types. The 0.45-0.50 μm band is in a ferrous iron absorption band, and is thus useful for detection of ferrous iron containing materials.

If the identification of various minerals is prioritized according to some measure of economic importance such as construction material (silicates, especially sand), iron ore (Ferric + Ferrous), heat balance and vegetation rejector, and carbonate (limestone), the channel priorities shown in Table 3-26 are obtained.

3.5 WATER AND MARINE RESOURCES

The selection of spectral band placement and bandwidth for water and marine resources depends on the phenomena to be delineated. The assumed objective of water resources applications for this study was

TABLE 3-25. LITERATURE SURVEY RESULTS - GEOLOGY



LITERATURE SURVEY RESULTS - GEOLOGY

TABLE 3-25A. LITERATURE SURVEY RESULTS - GEOLOGY
OPTIMUM SPECTRAL BANDS (μm)

THEORETICAL

Ross, Adler, Hunt	Vincent	Kondratyev, et al
0.50	8.1 - 9.2	0.6 - 0.7
1.45	8.2 - 10.2	0.8 - 1.1
1.95	9.3 - 11.3	
2.35	9.8 - 11.2	
no Δλ specified		

EMPIRICAL

Vincent	Dillman, Thomson	Dillman, Vincent, Hasell
0.5 - 0.54	0.44 - 0.47	0.43 - 0.47
0.63 - 0.69	0.54 - 0.56	0.49 - 0.51
1.0 - 1.4	1.0 - 2.6	0.63 - 0.67
1.5 - 1.8		2.0 - 2.5
2.0 - 2.6		8.0 - 9.1
		8.8 - 10.5

SYSTEMS STUDIES

EOSPDG	Advanced Scanners and Imaging Systems	SEOS
0.45 - 0.55	0.44 - 0.55	0.40 - 0.50
0.55 - 0.65	0.68 - 0.80	0.52 - 0.56
0.65 - 0.75	0.80 - 1.0	0.62 - 0.68
0.75 - 0.85	8.0 - 9.5	0.80 - 1.1
0.85 - 1.10	10.5 - 14.0	1.0 - 1.4
1.10 - 1.35		2.0 - 2.3
1.55 - 1.80		8.3 - 9.3
2.05 - 2.35		10.5 - 12.5
2 bands between 10.4 - 12.6		

TABLE 3-26. RECOMMENDED OPTIMUM BANDS FOR GEOLOGY (PRIORITIZED)

8.3 - 9.3
10.4 - 1.25
0.63 - 0.69
0.52 - 0.56
1.1 - 1.35
0.8 - 1.1
1.55 - 1.75
2.05 - 2.35
0.45 - 0.50

assessment of water quality. The minimum requirements for water quality determination are assessment of aquatic vegetation and algae concentration (chlorophyll), transparency suspended solids concentration, temperature gradients, and oil detection.

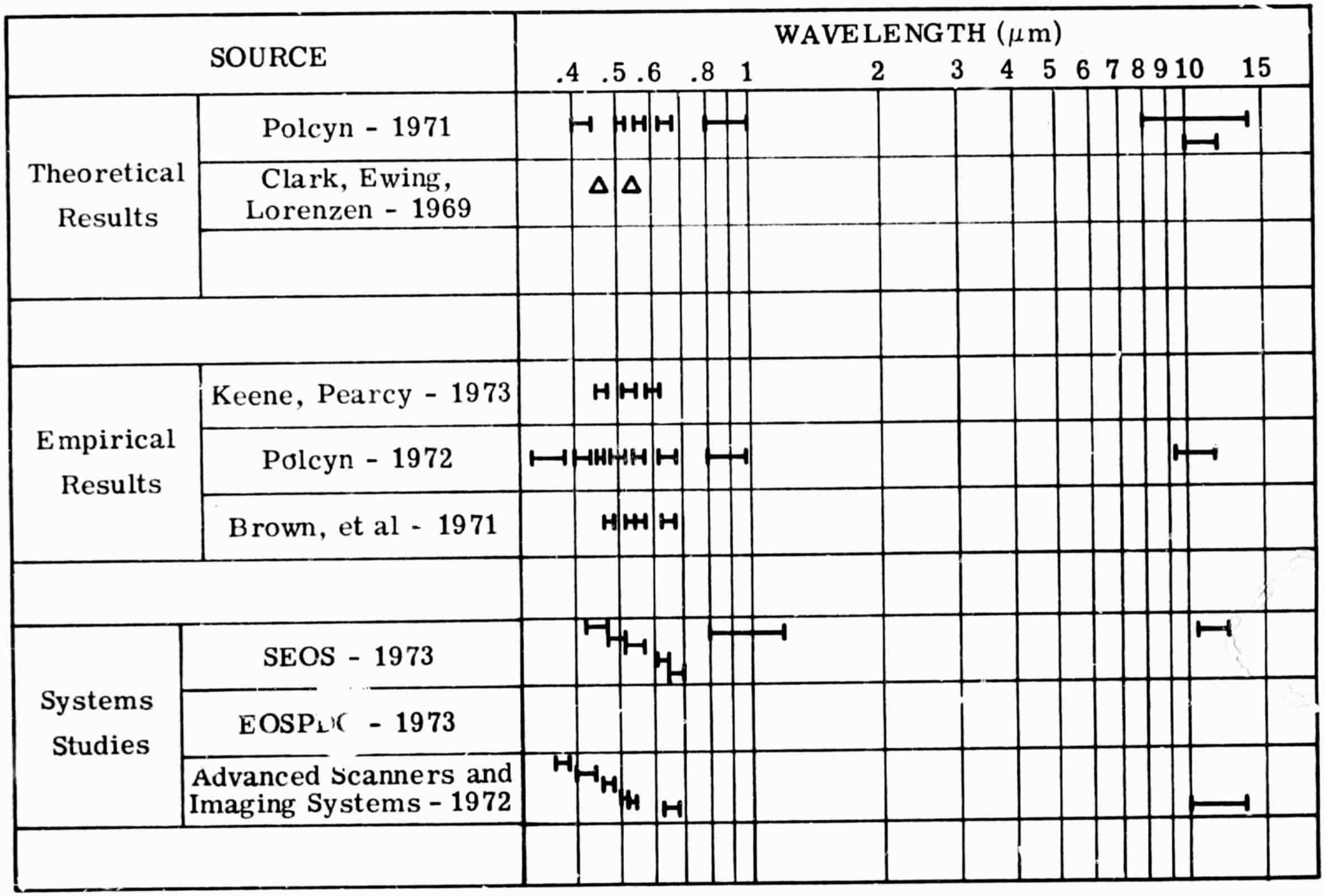
The primary objective of Water/Marine discipline applications was assumed to be Marine and Coastal Zone water surveys. In view of these objectives, bands which are indicators of aquatic vegetation will receive higher priority than in water resources applications because of coastal zone requirements. Similarly bands found to be indicators of oil, hence associated marine life or spills by tankers will receive higher priority than in the water resource discipline.

Limited empirical evidence for band selection was achieved with MSDS data from the Atchafalaya River and delta test site in Louisiana. Because of data quality aspects of the empirical study, prime reliance was placed on the literature survey and theoretical results in deriving the recommended spectral bands.

The literature survey results are presented in Tables 3-27A and 3-28A and in more graphical form for easy comparison in Tables 3-27 and 3-28. Before beginning a discussion of these results or presenting the empirical study results, let us give the recommended spectral bands in order of priority for each of these two discipline areas. The recommended bands for Water Resources are:

0.48-0.52 μm	0.42-0.48 μm
0.52-0.58 μm	0.58-0.64 μm
0.62-0.68 μm	0.69-0.74 μm
10.40-12.5 μm	0.50-0.54 μm
0.80-1.10 μm	0.32-0.38 μm

TABLE 3-27. LITERATURE SURVEY RESULTS – MARINE/OCEAN



LITERATURE SURVEY RESULTS - MARINE/OCEAN

TABLE 3-27A. LITERATURE SURVEY RESULTS - MARINE AND OCEAN OPTIMUM SPECTRAL BANDS (μm)

THEORETICAL

Polcyn	Clarke, Ewing, Lorenzen	Keene, Pearcy
0.40 - 0.44	0.46 no Δλ	0.45 - 0.47
0.50 - 0.52	0.54 specified	0.52 - 0.55
0.55 - 0.58		0.58 - 0.63
0.62 - 0.68		
0.80 - 1.00		
8.00 - 14.00		
10.00 - 12.00		

EMPIRICAL

Polcyn	Brown, et al
0.32 - 0.38	0.47 - 0.48
0.40 - 0.44	0.52 - 0.55
0.45 - 0.47	0.55 - 0.58
0.50 - 0.52	0.63 - 0.68
0.55 - 0.58	
0.62 - 0.68	
0.80 - 1.00	
9.30 - 11.70	

SYSTEMS STUDIES

Advanced Scanners and Imaging Systems	SEOS
0.36 - 0.39	0.42 - 0.48
0.40 - 0.45	0.48 - 0.52
0.46 - 0.49	0.52 - 0.58
0.49 - 0.52	0.62 - 0.66
0.52 - 0.56	0.66 - 0.70
0.64 - 0.68	0.80 - 1.20
10.10 - 14.00	10.50 - 12.50

TABLE 3-28. LITERATURE SURVEY RESULTS – HYDROLOGY/WATER RESOURCES

SOURCE		WAVELENGTH (μm) .4 .5 .6 .8 1 2 3 4 5 6 7 8 10 15
Theoretical Results	Wezernak - 1974	
	Mitsch - 1973	
	Kondratyev et al - 1973	
Empirical Results	Brown, Thomson, Thomson - 1969	
	Wezernak, Polcyn 1970	
	Wezernak, Lowe, Polcyn - 1967	
Systems Studies	SEOS - 1973	
	EOSPDG - 1973	
	Advanced Scanners and Imaging Systems - 1972	

LITERATURE SURVEY RESULTS - HYDROLOGY/WATER RESOURCES

TABLE 3-28A. LITERATURE SURVEY RESULTS - HYDROLOGY/WATER RESOURCES OPTIMUM SPECTRAL BANDS (μm)

THEORETICAL

Wezernak	Mitsch	Kondratyev, et al
0.42 - 0.48	0.30 - 0.45	0.70 - 0.8
0.50 - 0.54	0.41 - 0.47	0.80 - 1.1
0.63 - 0.70	0.54 - 0.58	
	0.62 - 0.67	
	0.63 no $\Delta\lambda$	
	0.65 no $\Delta\lambda$	
	8.00 - 14.00	

EMPIRICAL

Brown, Thomson	Wezernak, Polcyn	Wezernak, Lowe, Polcyn
0.42 - 0.46	0.40 - 0.44	0.32 - 0.38
0.52 - 0.55	0.44 - 0.46	0.40 - 0.44
0.58 - 0.62	0.55 - 0.58	0.55 - 0.58
0.66 - 0.72	0.58 - 0.62	0.62 - 0.68
0.52 - 0.66	0.66 - 0.72	0.80 - 1.00
	0.72 - 0.80	
	8.00 - 10.00	

SYSTEMS STUDIES

SEOS	EOSPDG	Advanced Scanners and Imaging Systems
0.42 - 0.48	0.50 - 0.60	0.48 - 0.64
0.48 - 0.52	0.60 - 0.70	0.80 - 1.10
0.52 - 0.58	0.80 - 1.10	8.0 - 14.0
0.60 - 0.70	10.4 - 12.6	
0.80 - 1.10		
2.0 - 2.30		
10.5 - 12.5		

and recommended bands for Marine Resources are:

0.62-0.68 μm	0.80-1.10 μm
0.48-0.52 μm	0.58-0.64 μm
0.42-0.48 μm	0.69-0.74 μm
10.40-12.5 μm	0.50-0.54 μm
0.52-0.58 μm	0.32-0.38 μm

For the assessment of the concentration of suspended solids, measurements are required in the 0.48-0.52 μm, 0.52-0.58 μm, and 0.63-0.68 μm bands. The 0.48-0.52 μm and 0.62-0.68 μm bands are also indicators of chlorophyll content, hence aquatic vegetation or phytoplankton. The 10.4-12.5 μm thermal band is an indicator of water temperature. The 0.80-1.1 μm band is useful in delineating land-water interfaces. The 0.42-0.48 μm band, along with the 0.58-0.64 and 0.69-0.74 μm regions are used for the detection of algae blooms (the 0.58-0.64 μm is a peak reflectance region for the "red tide" phenomenon). The 0.50-0.54 μm region is useful in water depth measurements and may provide baseline information on the detection of phytoplankton concentrations. The use of the 0.32-0.38 μm band for oil detection is probably not feasible from satellites. It is however, a desirable band for water and marine resource users as an indication of presence of oil.

The optimum bands for Marine/Ocean applications differ from water resource bands only in priority. The bands for detection and identification of aquatic vegetation were given higher priority in marine resources than water resources because of the stated objective of Coastal Zone water surveys where this information is very important.

Atchafalaya Empirical Study

Scanner data and ground truth problems seriously limited the scope of this water study. Examination of 7 x 7 reconnaissance graymaps of the two MSDS flightlines flown over the test site on 19 September 1973 revealed that the targets of interest were in the first two thirds of

flightline 1. It was decided, in the interests of increased efficiency and reduced cost, to restrict further aircraft data processing to this subset of data.

Upon detailed examination the MSDS data was found to have several general problems associated with it that compromised its usefulness for this study. The most important problem was a condition described as the "sticky bit" phenomenon. This caption describes the presumed source of the problem and refers to the preference exhibited by the MSDS for having a certain digital bit turned on during the in-flight analog-to-digital data conversion. The least significant bit was found to be affected in this manner in all channels except for channel 1.

The effects of this problem can be observed in Table 3-29, where it is described as a "cycle of 2" striping pattern in the data histograms. Unfortunately, this problem was not confined to the least significant bit, as evidenced by the appearance of a "cycle of 4" striping pattern, indicating that the second least significant bit is similarly affected. In general, however, this cycle of 4 is much less pronounced.

Since this condition would seriously compromise the performance of standard pattern recognition techniques it was felt necessary to remove it. This was accomplished by dividing each original data value by 2 and then rounding to the nearest integer value. The results is a data set with a dynamic range reduced by one half, but with the relative significance of the original signal maintained. In effect, the data, which originally had 8 bits significance, now had 7 bits significance.

At this point it should also be pointed out that, even before scaling, the sensor's nominal dynamic range was never more than 50% utilized.

Finally, it was also necessary to omit 5 of the 20 available spectral bands for other problems: channel 7 (2.10-2.36 μm) - no

TABLE 3-29. MSDS DATA QUALITY
ATCHAFALAYA DATA

TAPE CHANNEL	$\lambda_1-\lambda_2$	DYNAMIC RANGE (0-256) (DATA VALUES)	%	HISTOGRAM STRIPING PATTERN DUE TO "STICKY BIT"	OTHER
1	.34-.40	114-147	13	Not apparent	
2	.46-.50	87-111	10	Cycle of 2*	
3	.57-.63	69-.67	39	Cycle of 4**	
4	.71-.75	49-147	39	Cycle of 4	
5	.82-.87	35-159	49	Cycle of 4	
6	1.18-1.30	37-123	34	Cycle of 4	
7	2.10-2.34	0	0		No data
8	4.50-4.75	0-77	30	Cycle of 4	%.74 clipped L.L.***
9	9.30-9.80	13-55	17	Cycle of 4	
10	11.00-12.00	19-99	32	Cycle of 4	
11	1.12-1.16	0-57	23		.23% clipped L.L.
12	.40-.44	112-140	11	Every 4th bin	
13	.53-.57	81-163	32	Cycle of 4	
14	.64-.68	51-137	46	Cycle of 2	
15	.76-.80	41-147	46	Cycle of 4	
16	.97-1.05	36-154	46	Cycle of 4	
17	1.52-1.73	7-111	41	Cycle of 2	.18% clipped L.L.
18	3.54-4.00	3-33	12	Cycle of 4	1.04% clipped L.L.
19	6.00-7.00	0-137	54	Every other bin	26.5% clipped L.L.
20	10.10-11.00	19-51	13	Cycle of 4	
21	12.00-13.00	11-85	29	Cycle of 4	
22	1.05-1.09	23-155	52	Cycle of 4	*Lower Limit

*Least significant bit has a preferred value

**Second least significant bit has a preferred value

data; channel 12 (0.40-0.44 μm) and channel 19 (6.0-7.0 μm) - empty bins; and channel 8 (4.50-4.75 μm) and channel 11 (1.12-1.16 μm) - excessive data clipping.

Because of the compromises on the available data for the Atchafalaya test site, the spectral study for this data set was limited to a determination of the optimum 4 bands for coastal zone surveys. The separate sets of optimum bands shown in Table 3-30 were selected for water turbidity and for surrounding terrestrial cover including natural vegetation. Water turbidity was classified for four turbidity levels ranging from clean water to light, moderate, and heavy turbidity.

The terrestrial cover types examined logically separate into the three following general categories: (1) natural vegetation communities, (2) cultural vegetation, and (3) non-vegetation.

The natural vegetation types studied including the following:

1. Duckweed
2. Emergent vegetation
3. Water hyacinth
4. Young willows on newly accreted sites
5. Old willows
6. A mixture of cypress and tupelo completely flooded
7. A mixture of cypress and tupelo partially flooded
8. A stand of upland forest

Cultural vegetation types, in contrast, consisted of:

1. Upland grass
2. Sugar cane
3. Other crop (presumably rice)

The final category of cover types, which represents the non-vegetative targets included:

1. Stubble in a field of dry rice
2. Stubble in a field of wet rice
3. Dry bare soil

TABLE 3-30. OPTIMUM FOUR CHANNELS
ATCHAFALAYA COASTAL ZONE TEST SITE

WATER TURBIDITY

RANK	SPECTRAL CHANNEL	PAIRWISE PROBABILITY OF MISCLASSIFICATION
1	0.57 - 0.63 μm	0.013
2	0.71 - 0.75 μm	0.007
3	0.34 - 0.40 μm	0.005
4	0.46 - 0.50 μm	0.004

TERRESTRIAL COVER

RANK	SPECTRAL BAND	PAIRWISE PROBABILITY OF MISCLASSIFICATION
1	0.97 - 1.05 μm	0.060
2	0.40 - 0.50 μm	0.015
3	0.34 - 0.40 μm	0.008
4	1.18 - 1.30 μm	0.006

4. Wet bare soil
5. Clear water
6. Highly turbid water

The optimum four channels selected for the water turbidity segment of this study are shown in the top section of Table 3-30. The technique used for determining turbidity was a single band level slice. In the ranking of channels, a NIR band (0.71-0.75 μm) was the second best channel; this band provides information on organic material concentrations. The orange band (0.57-0.63 μm) was slightly better than the red band (0.64-0.68 μm), but this is explainable by the fact that the red band was noticeably noisy at low signal levels (determined by graymap inspection). The selection of the NIR band as the second best channel indicated that enough water penetration was still possible in that spectral band to provide some information regarding the presence of suspended organic material and possibly vegetation.

A ratio map of the orange/NIR band was made in an attempt to exploit this phenomenon and provide a means of organic turbidity discrimination and mapping. The orange band was substituted for the red band because it had a clearer signal.

For the natural and cultural vegetation targets and non-vegetation targets selected, only two spectral channels were needed to provide essentially all spectral discrimination of these cover types that is possible at this time of year (see the bottom of Table 3-30). The two bands that were selected were (1) a NIR band, 0.97-1.05 μm, and (2) a blue band, 0.46-0.50 μm. The choice of the blue band, in which chlorophyll absorption occurs, was presumably in lieu of the red band (0.64-0.68 μm) which is in the chlorophyll absorption band, and the one would expect to be selected in this type of work. But as previously noted, the red band was noisy in this data set. The choice of the NIR band is accounted for by the uniqueness of the canopy characteristics and backgrounds encountered in the vegetation types examined. The

1.18-1.30 μm was possibly selected as an aid in vegetative discrimination and the 0.34-0.40 μm band for turbidity determination, and for separation of the bare soil classes from the vegetation classes.

Table 3-31 shows the accuracy of delineating the four water quality categories using a slicing technique on the orange/NIR ratio. The very heavy turbidity class was most accurately recognized, the clear water class next most accurately recognized. The intermediate classes of turbidity showed the poorest recognition accuracy. The data of Table 3-31 were obtained on test set data, and water turbidity classes were delineated by photointerpretation.

As with many natural problems, the variation of water quality is continuous — attempts were made to break the quality into five levels by slicing an orange/NIR ratio. When a ratio is sliced into too many segments, poor accuracy results because the noise on the ratio exceeds the width of the slicing interval. Improved accuracy will result if fewer classes are used. Also there may be errors of ± 1 level of water quality in the photointerpretation used to pick the test sets.

As a result of these uncertainties, and in an effort to assess the accuracy of detection of sharp boundaries separating water masses of different quality, the mapped data were analyzed. The bottom of Table 3-31 shows the results of the analysis. The average accuracy of correct classification of the five classes of water quality is 48.1%. If misclassification of ± 1 water quality level is ignored, the accuracy increases to 85.2%. Indeed, the only water type not perfectly classified ± 1 level is the light turbidity class. The accuracy of detecting a boundary between water of different quality levels was 92%. This number was larger than the average accuracy of correct recognition of water quality types because of the large turbidity differences which exist across boundaries of water masses in rivers and lakes.

TABLE 3-31. TURBIDITY CLASS BOUNDARY DETECTOR ACCURACY FOR MSDS DATA

ATCHAFALAYA DATA SET

	CW	Lt. T	M.T.	H.T.	V.H.T.
Clear Water	45.5	36.4	18.2		
Light Turbidity	11.1	33.3	44.4	11.1	
Moderate Turbidity			41.7	25.0	33.3
Heavy Turbidity				18.2	72.7
Very Heavy Turbidity				9.1	90.1

Average Accuracy 48.1%

± 1 Class 85.2%

Identifying a boundary when one was present 92%

3.6 CONCLUSIONS AND RECOMMENDATIONS - SPECTRAL STUDY

Table 3-32 summarizes the priority spectral bands by discipline. It is a compilation of several tables which have appeared in this section of the report. In examining the requirements of each discipline, there are several consensus bands which every discipline needs.

A band of 0.63-0.69 μm is high on the list of every discipline. This band is required for the detection of chlorophyll absorbtion in vegetation and in phytoplankton. Additionally, it serves a useful purpose in geology by assisting in the detection of ferric iron containing materials.

A thermal band in 10.4-12.5 μm also seems high on the list in each discipline. This broad, radiometric temperature measuring band is also useful as one component of a two thermal band reststrahlen detection scheme for determining the presence and nature of silicate minerals for geology. The second thermal band for the geologic application is 8.3-9.3 μm, in the middle of the reststrahlen emissivity dip for pure quartz.

A third consensus band in all disciplines is a 0.75-0.95 μm band. This is useful for vegetation classification because it covers the near infrared high reflectance plateau, useful for delineating water-land boundaries because of the large differential reflectance between water and land, and useful to some extent in geology for mapping materials containing ferric iron and for delineating vegetation cover on rock surfaces. It is recommended that the lower edge of the band be moved from .75 to .80 to improve land water interface delineation.

A band in the 0.55-0.60 μm or 0.52-0.58 μm region rates high on the list for all disciplines except urban land use. In agriculture, the band is useful for assessing the growth state of vegetation by monitoring the green reflectance peak. In the water resources, the band can be used in a turbidity estimation algorithm and to measure water

TABLE 3-32. PRIORITIZED SPECTRAL BANDS BY DISCIPLINE

AG/RANGE/FORESTRY	WATER RESOURCES	MARINE/OCEAN	GEOLOGY	URBAN LAND USE
.63 - .69 μm	.48 - .52 μm	.62 - .68 μm	8.3 - 9.3 μm	10.4 - 12.5 μm
.75 - .95 μm	.52 - .58 μm	.48 - .52 μm	10.4 - 12.5 μm	.8 - 1.1 μm
10.4 - 12.5 μm	.62 - .68 μm	.42 - .48 μm	.63 - .69 μm	.63 - .69 μm
.55 - .60 μm	10.4 - 12.5 μm	10.4 - 12.5 μm	.52 - .56 μm	.5 - .54 μm
*1.55 - 1.75 μm	.8 - 1.1 μm	.52 - .58 μm	2.05 - 2.35 μm	2.05 - 2.35 μm
2.05 - 2.35 μm	.42 - .48 μm	.8 - 1.1 μm	.8 - 1.1 μm	.42 - .48 μm
.69 - .75 μm	.58 - .64 μm	.58 - .64 μm	1.55 - 1.75 μm	.58 - .64 μm
	.69 - .74 μm	.69 - .74 μm	1.1 - 1.35 μm	
	.5 - .54 μm	.50 - .54 μm	.45 - .50 μm	
	.32 - .38 μm	.32 - .38 μm		

*or 2.05 - 2.35

depth. In the Geology discipline, the 0.52-0.56 μm band is useful in the detection of ferric iron compounds (in conjunction with the 0.63-0.69 μm band).

The last consensus band is one in the near infrared portion of the spectrum. There is a slight preference for 2.05-2.35 μm in Geology and Urban Land Use, for the detection of hydroxyl ions and man-made features respectively. However, the engineering difficulties in obtaining an adequate signal to noise ratio in this band appear to be such as to bias desires in favor of a 1.55-1.75 μm band. As previously noted, for vegetation vigor assessment, either 1.55-1.75 μm or 2.05-2.35 μm bands are acceptable.

The water resources, marine/ocean, geology, and urban land use disciplines rated bands in the 0.42-0.52 μm region as high priority. A single compromise band of 0.45-0.52 μm would satisfy these disciplines with little degradation of information requirements. The lower end of this compromise band should be shifted to 0.45 μm to reduce scattering effects of shorter wavelengths.

Beyond these six bands, a further consensus is difficult to identify. Depending on the discipline, a seventh band might be 8.3-9.3 μm (for reststrahlen detection and better water temperature estimates) or 0.42-0.48 μm (for more accurate delineation of chlorophyll and suspended solids concentration).

The above analysis suggests a seven band scanner system for the EOS thematic mapper. The proposed set of bands is different from the baseline specifications in that some of the bands are narrowed, the 2.05-2.35 μm band is replaced with a blue-green band, and the 0.7-0.8 μm band is replaced with either a blue or a second thermal (8.3-9.3 μm) band. The bands are listed in Table 3-33.

TABLE 3-33. RECOMMENDED SPECTRAL BANDS[1] (PRIORITIZED)

0.63 - 0.69 μm
0.80 - 0.95 μm
10.4 - 12.5 μm
0.52 - 0.60 μm*
1.55 - 1.75 μm
0.45 - 0.52 μm†
0.42 - 0.48 or 8.30 - 9.30 μm

[1] Optimized for Agriculture, Water Resources and Land Use.

* Compromise between 0.55 - 0.60 μm and 0.52 - 0.58 μm.

† Compromise between 0.42 - 0.48 μm and 0.48 - 0.52 μm.

C-2

4
RADIOMETRIC REQUIREMENTS STUDY

4.1 GENERAL

This aspect of the systems study addressed various user discipline needs for data calibration, stability, and signal sensitivity. Or in other words, the amount of data miscalibration, instability, and noise which could be tolerated in different remote sensing applications using multispectral scanners to measure spectral radiance. These sources of error in the recorded signal levels of a scanner can cause such sizeable problems to occur in the automatic classification of features within a scene that little information is obtained. The interaction between these sources of signal inaccuracy and the classification accuracy which can be obtained for a given user application must be understood and taken into account in the scanner design to produce optimum or even acceptable information for the user. It is the user requirement for classification accuracy which defines the acceptable error or instability in sensor parameters.

Variations in (1) recording precision, (2) gain and offset, and (3) noise level of scanner data were examined in an empirical manner to determine the signal accuracy required of an assumed optimum seven-spectral band orbital scanner for each of the five separate user disciplines. In addition, theoretical calculations were carried out for water quality and water depth mapping applications to estimate the noise equivalent reflectance difference (NE$\Delta\rho$) required in various spectral bands to achieve the information extraction performance required. The noise equivalent reflectance (or temperature) difference (NE$\Delta\rho$) is the change in ground reflectivity which produces a signal equal to the scanner noise, e.g., S/N = 1. Achieving low NE$\Delta\rho$ MSS systems for satellites is costly and affects the size of the optics and number of detectors per spectral band. Therefore, some guidelines are very important.

4.2 DISCUSSION OF RADIOMETRIC PRECISION DATA

One method of simulating MSS data with various sensitivity levels is to change the signal-to-noise ratio by changing the digital representation of the data. Reduced sensitivity levels can be simulated by reducing the number of binary places or bits in the digital form leaving fewer significant places to the signal. Thus we are simulating instrument noise with quantization noise (for data sufficiently free of instrument noise).

Simulated orbital MSS data from both Baltimore and Michigan were processed to demonstrate the effect of improved or reduced data significance on the correct classification of urban land use and agriculture categories. Through ground radiometric measurements taken concurrently with acquisition of the multispectral scanner data, the quantum equivalent reflectance difference($QE\Delta\rho/\Delta T$) of one bin width in each spectral band was calculated. For the thermal band, the temperature difference associated with one bin width was computed.

By calculating the quantum equivalent reflectance of one bin width, the quantum equivalent reflectance of bins which were twice and four times as wide as the original digitized bin width are also known. These correspond to the cases where the least significant one and two bits (and three and four bits for the Michigan data) were dropped from the data to simulate data having various noise equivalent reflectance differences ($NE\Delta\rho$) as might be characteristic of different MSS systems.

Procedure

Eight- and seven-bit data sets were generated for seven optimum channels of the simulated orbital 30 m data. The seven bands used were optimum for the 9-bit data. Then signatures were extracted from each data set using identical training locations to those used for the 9-bit data. (The 7- and 8-bit data were generated by dividing data values in the seven optimum channels by 2 and 4, then truncating the fractional

part of the quotient. Such a procedure effectively reduces the significance of the data by 1 and 2 bits respectively.)

Classification was carried out on the data using signatures extracted from each data set. Accuracy figures on test areas removed from training areas were tabulated for each level of significance.

Results

Tables 4-1 and 4-2 show the quantum equivalent $\Delta\rho$ and ΔT for one bin width at each level of data significance for both Baltimore Land Use and Michigan Agriculture data. The change in reflectance on the ground corresponding to a given change in radiance received by the scanner, calculated from the ground truth data for these two data sets, was multiplied by the change in radiance represented by one signal count level to obtain the QE$\Delta\rho/\Delta T$ values listed in Table 4-1 and 4-2. The reflectance or temperature corresponding to one bin width gets larger by a factor of 2 every time an additional low order bit is dropped.

Figures 4-1 and 4-2 show the effect on test area recognition accuracy for the Baltimore Land Use and the Michigan Agriculture data, respectively. In the Baltimore results there is very little effect on classification accuracy as we go from 9-bit to 7-bit data. The Level I classes are not affected, and there is only a slight drop in the accuracy of recognition of the Level III classes. This indicates that NE$\Delta\rho/\Delta T$ values equal to the QE$\Delta\rho/\Delta T$ values found by multiplying by 2 the values in the 7-bit column of Table 4-1, should be appropriate for Land Use mapping. These average less than two percent NE$\Delta\rho$. Although further reduction of data significance was not carried out, the expectation is that Level III accuracy would not drop quickly until the 5-bit case if the data were reduced in significance over the 7-bit case, and that Level II recognition accuracy would also not be affected until the 5-bit case. Further experiments are required to show exactly the quantitative nature of the recognition performance

TABLE 4-1. EQUIVALENT $\Delta\rho$ (ΔT) FOR BALTIMORE DATA SIGNIFICANCE STUDY

CHANNEL	Equivalent $\Delta\rho$ (ΔT) 9 BIT †	8 BIT †	7 BIT †
*.41 - .48	.00079	.00158	.00316
*.46 - .49	.00085	.00170	.00340
.48 - .51	.00083	.00165	.00330
.50 - .54	.00092	.00185	.00369
.52 - .57	.00112	.00224	.00447
.55 - .60	.00108	.00216	.00432
.58 - .64	.00074	.00148	.00296
*.62 - .70	.00101	.00202	.00404
*.67 - .94	.00280	.00560	.01120
* 1 - 1.4	.0188**	.0376**	.0752**
*1.5 - 1.8	.0082*	.0164**	.0328**
*9.3 - 11.7	0.043°K	0.086°K	0.17[illegible]°K

* Channels used in analysis.

**Data values in this channel subject to considerable uncertainty because of uncertainty of irradiance measurement.

† This number does not reflect the data word size in a real sense, but is only a method of simulating the NE$\Delta\rho$(ΔT).

TABLE 4-2. EQUIVALENT $\Delta\rho$ (ΔT) FOR MICHIGAN AGRICULTURE DATA SIGNIFICANCE STUDY

CHANNEL	9 BIT †	8 BIT †	7 BIT †	6 BIT †	5 BIT †
*.41 - .48	.00057	.00115	.00230	.00460	.00920
.46 - .49	.00029	.00058	.00116	.00232	.00464
.48 - .51	.00039	.00079	.00158	.00316	.00632
.50 - .54	.00036	.00072	.00144	.00288	.00576
.52 - .57	.00034	.00068	.00136	.00272	.00544
*.55 - .60	.00037	.00073	.00146	.00292	.00584
.58 - .64	.00037	.00074	.00148	.00296	.00592
*.62 - .70	.00043	.00086	.00172	.00344	.00688
*.67 - .94	.00171	.00341	.00462	.00924	.01848
* 1 - 1.4	.00094	.00187	.00374	.00748	.01496
*1.5 - 1.8	.00108	.00216	.00432	.00864	.01728
*9.3 - 11.7	.032°K	.063°K	.126°K	.252°K	.540°K

*Channels used in the study.

.00115 = 0.115% equivalent reflectance difference.

†This number does not reflect the data word size in a real sense, but is only a method of simulating the NE$\Delta\rho$ (ΔT).

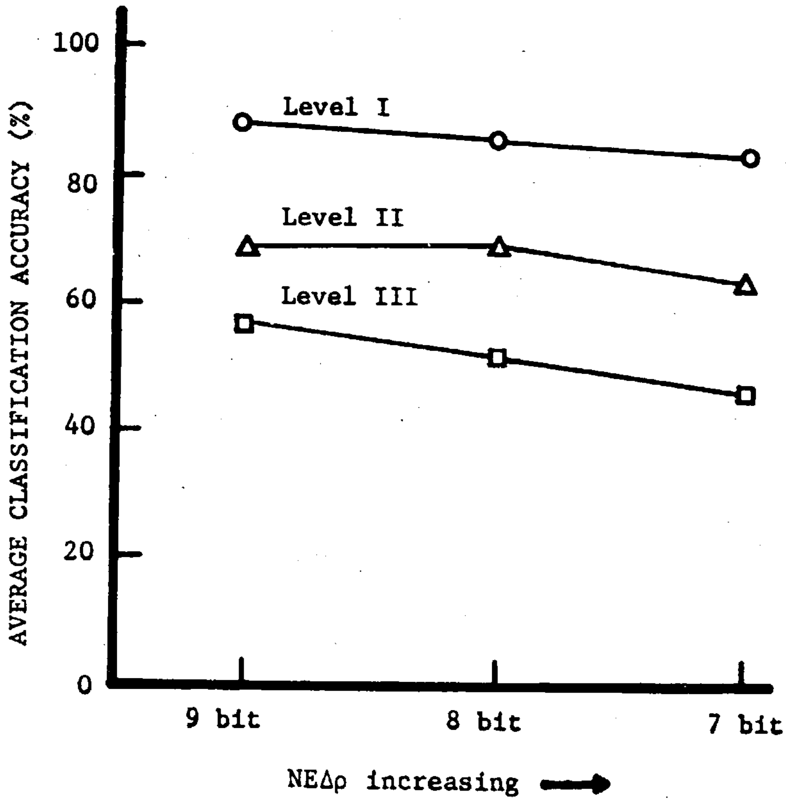


FIGURE 4-1. EFFECTS OF INCREASING NEΔρ (NEΔT) ON THREE ANDERSON LEVELS OF LAND USE CLASSIFICATION

BALTIMORE DATA 28.8 m, 7 OPTIMUM CHANNELS

1345 hours

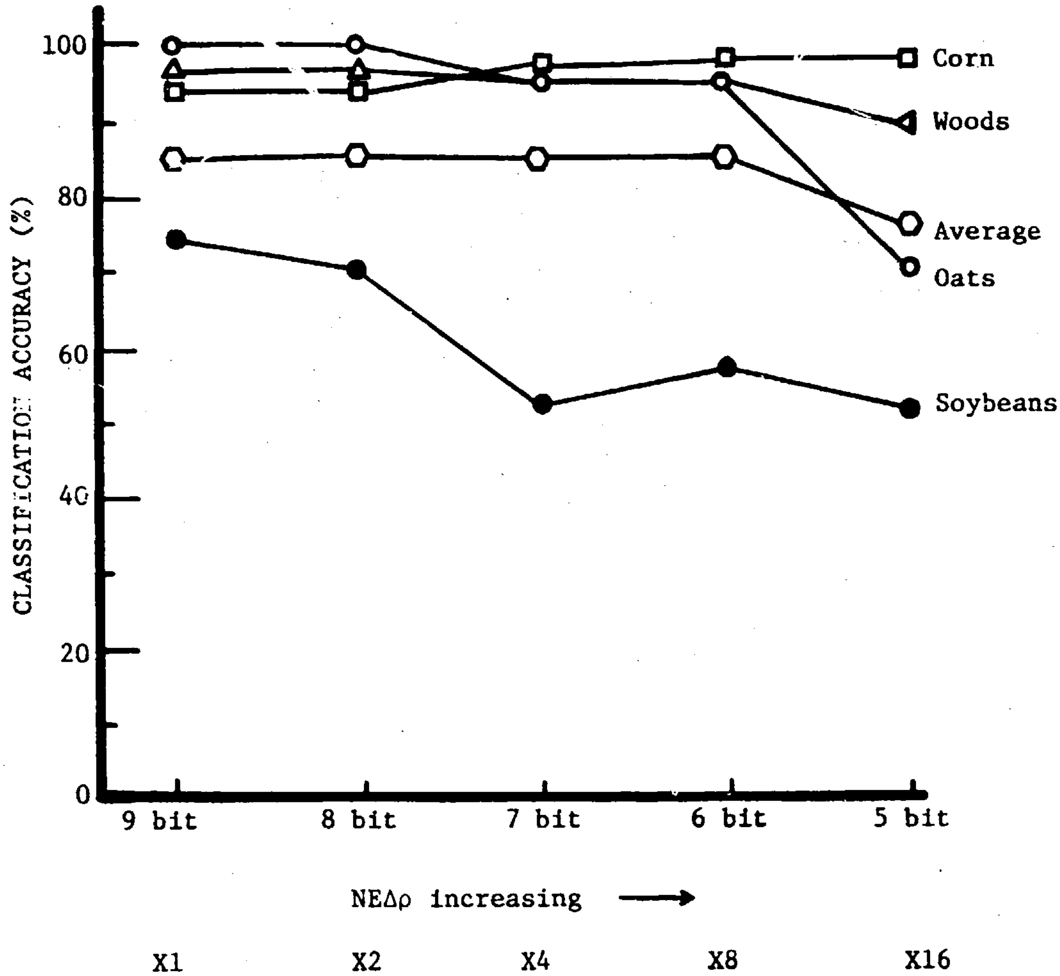


FIGURE 4-2. INCREASING NEΔρ versus DECREASING CLASSIFICATION ACCURACY FOR AGRICULTURE

MICHIGAN DATA 30 m
7 OPTIMUM BANDS (OPTIMIZED FOR 9 BIT DATA)
8/15/73 - 1130 HOURS

degradation. Performance matrices showing the correct classification accuracy and the errors of commission and omission by class are given in appendix A.

The recognition of representative crops and fields (Figure 4-2) does not seem materially affected by dropping three bits of data significance. Thus the QE$\Delta\rho$ and QEΔT numbers shown in Table 4-2 under the 6-bit column probably represent better NE$\Delta\rho$/ΔT performance than is actually required to map these crop types. Dropping an additional bit of significance does begin to have a small effect on crop and field recognition, however, as one might expect. The 5-bit performance probably is acceptable. The average NE$\Delta\rho$ for the 5-bit data is about 0.6 percent in the visible and 1.5 percent in the near IR bands where vegetation reflectance is higher. This result from the empirical study is taken into account in the user radiometric results presented in section 4.6.

4.3 DISCUSSION OF "GAIN" AND "OFFSET" STUDIES

The basic automatic pattern recognition approach to the classification of terrain materials rests on the premise that the spectral reflectance patterns of scene materials are characteristic of these classes of materials and are different enough to permit their separation by statistical decision approaches. In a typical remote sensing implementation, the spectral radiance of scene materials is measured in discrete wavelength bands by a sensor physically removed from the objects. The objects are illuminated by the sun and reflect, or emit energy which is detected by the sensor after passage through the atmosphere.

In supervised and unsupervised pattern recognition, the classifier must first be taught what patterns to recognize before it can realistically classify unknown data. Usually, the classifier is trained by extracting class statistics from known scene areas, either by normally

identifying training sets (supervised) or by clustering procedures (unsupervised). A key assumption in the pattern recognition approaches is that the spectral radiance of materials, as measured at the sensor, are representative of the materials. Thus, once trained, the processor expects to see the same spectral radiance from, e.g., a corn field, as it saw from the training set corn field.

But factors not under control of the user can influence the radiance the sensor measures from the scene materials and the resultant sensor output electrical signals on which the pattern recognition classifiers operate. These factors change the transfer function between scene reflectance and the sensor output voltages. (The Transfer function is assumed invariant for pattern recognition approaches other than adaptive ones). Basically, the relationship between scene reflectance and sensor output voltage is linear:

$$V = A + M \rho$$

Factors contributing to the additive term $\underline{A}$ are sensor bias factors and the path radiance in the atmosphere. Factors contributing to the multiplicative factor $\underline{M}$ are sensitivity (volts/watt), solar illumination, and atmospheric transmission. Variations in any of these sensor, atmospheric, or illumination parameters can change the transfer function between scene reflectance and scanner output voltage and thus invalidate the assumption of a constant transfer function. The variations will have serious effect when they occur between the collection of training set data and the collection of the unknown data to be classified because they are generally unknown and destroy the ability of the processor to achieve acceptable classification accuracy.

Regardless of what causes the transfer function to vary, it is of interest to know the effect of such variations on the classifier performance. It was assumed for this study, that the variations occurred in parameters of the simulated orbital MSS systems between training and classification of unknown data. The "gain" study modelled

the effects of varying the above coefficient M on the classification accuracy. The "offset" study modelled the effect of varying the coefficient A.

Studies were performed for the Baltimore Land Use and the Michigan Agriculture data sets. Gain and offset were varied independently and the result on test set classification noted. The signature areas used were the same as for the 30 m, 7 optimum channel data previously discussed, and on which this study was performed. Rather than vary the data, the signatures were varied to simulate the gain and offset variations. Each parameter was varied by amounts related to the average signature's separability for the classes considered, primarily to obtain reasonable ranges of classifier accuracy variation. Table 4-3 relates the nomenclature of the graphs to be presented to the actual variation in gain (in percent) and offset (as a percentage of the sensor dynamic range) for the two cases studied.

Figures 4-3 and 4-4 summarize the results in graphical form for the Baltimore Land Use data, and Figures 4-5 and 4-6 for the Michigan Agriculture data. Appendix A contains the detailed performance matrices. Referring to the Baltimore data, the general effect of both gain and offset variations (away from the conditions of training, represented by zero) is a reduction of classification accuracy. Generally the curves are not symmetrical about the zero point. This occurs for at least two reasons. First the actual distribution of test set points is not Gaussian and does not necessarily have the same mean and standard deviation as the training set. Second, the detailed behavior of classification results depends on the structure of the decision space. If decision boundaries are not located symmetrically around distributions, the effects of increasing and decreasing offset or gain will be different. As gain and offset are varied, the major feature of the classification results is the rapid increase in the size of the not classified category. At $\pm$ 2/3 gain or offset, nearly

TABLE 4-3. GAIN OFFSET VARIATIONS FOR BALTIMORE LAND USE AND MICHIGAN AGRICULTURE CASES

	Gain Variation (Graphs)	Percent Variation in Sensor Gain
Baltimore:	± 1/3	19.4
	± 2/3	38.8
Michigan:	± 1/3	7.1
	± 2/3	14.2

	Offset Variation (Graphs)	Percent of Sensor Dynamic Range
Baltimore:	± 1/3	3.3
	± 2/3	6.6
Michigan	± 1/3	1.9
	± 2/3	3.8

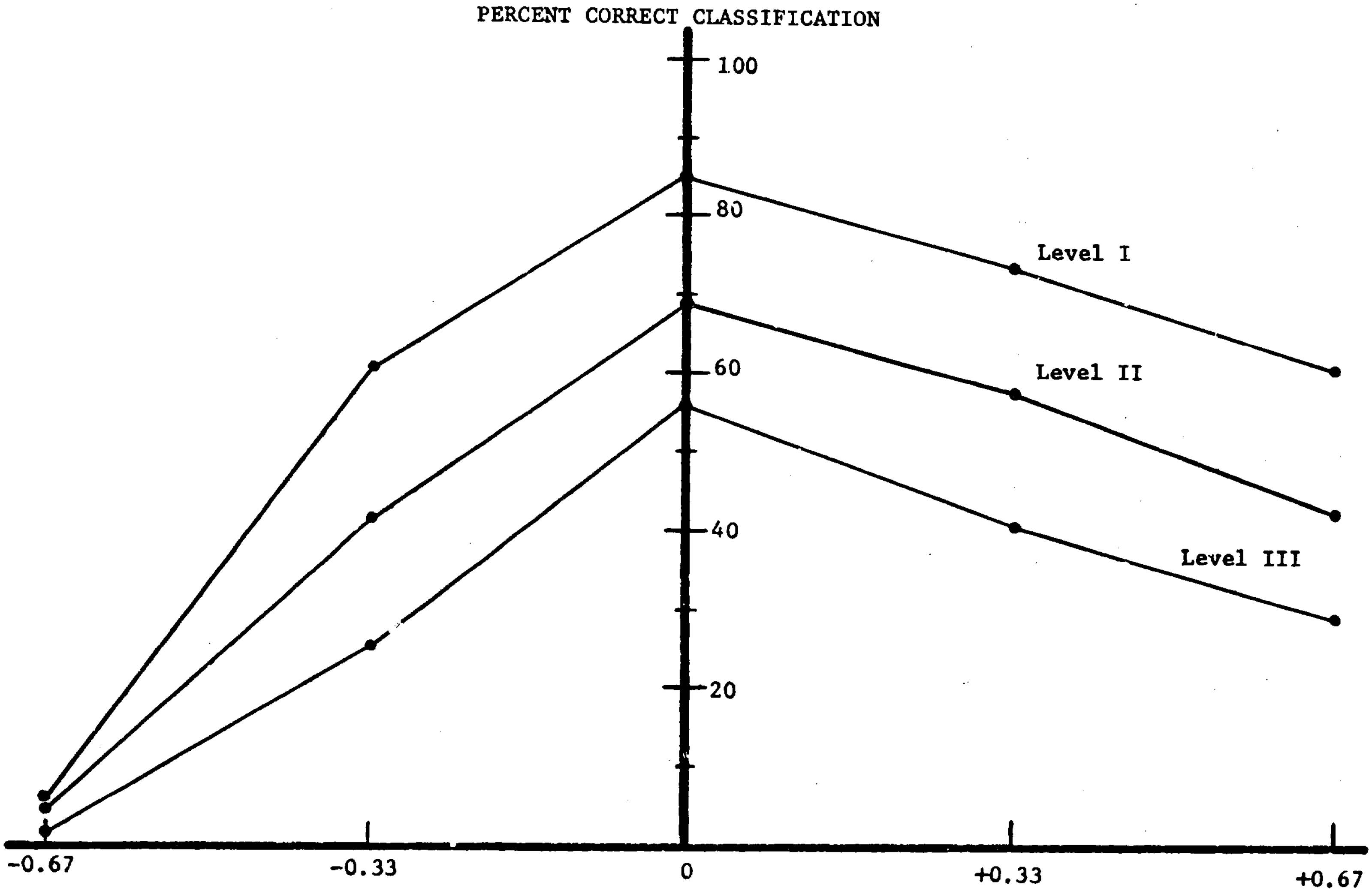


FIGURE 4.3. EFFECT OF GAIN VARIATION ON BALTIMORE CLASSIFICATION RESULTS

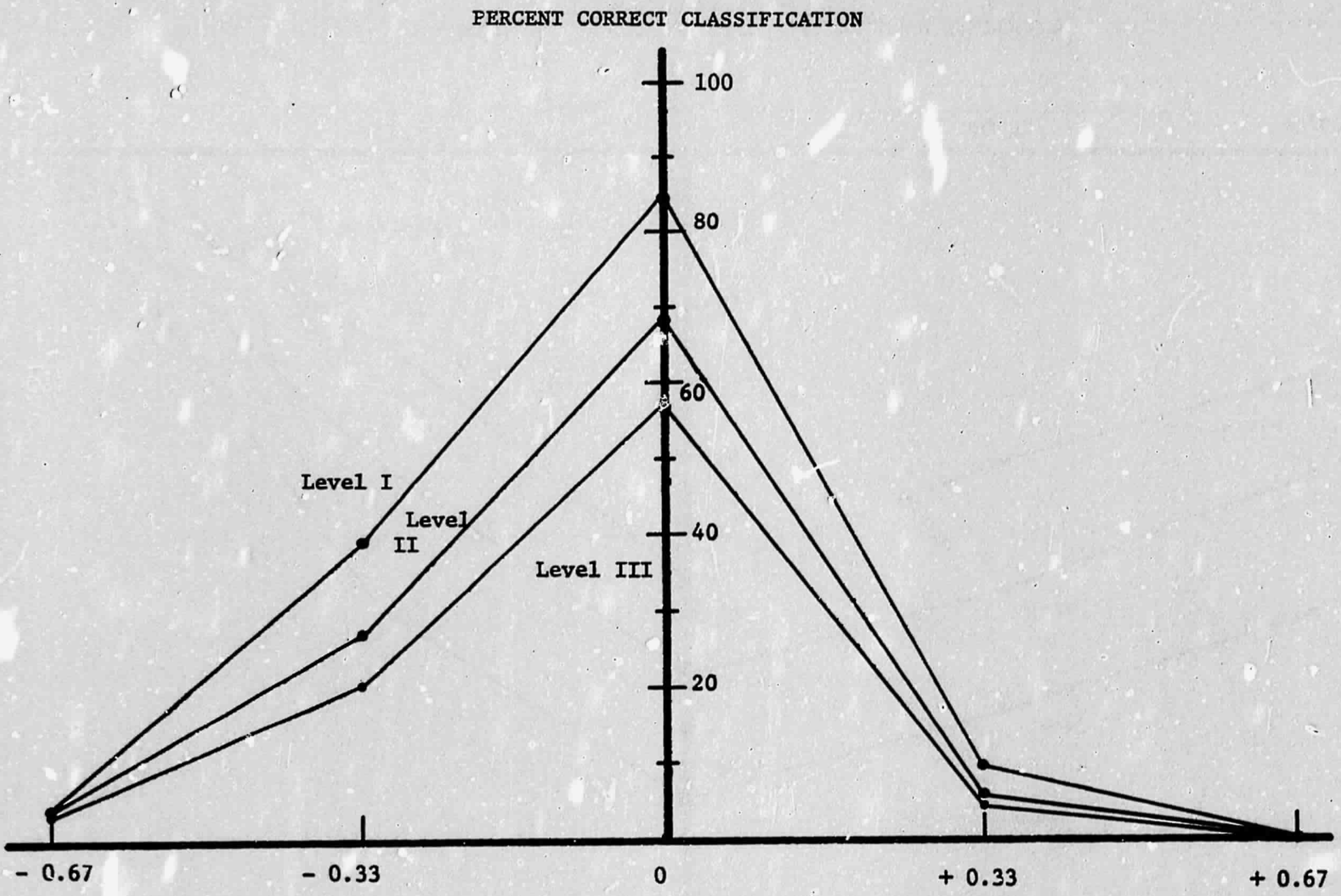


FIGURE 4-4. OFFSET VARIATION EFFECTS ON BALTIMORE CLASSIFICATION

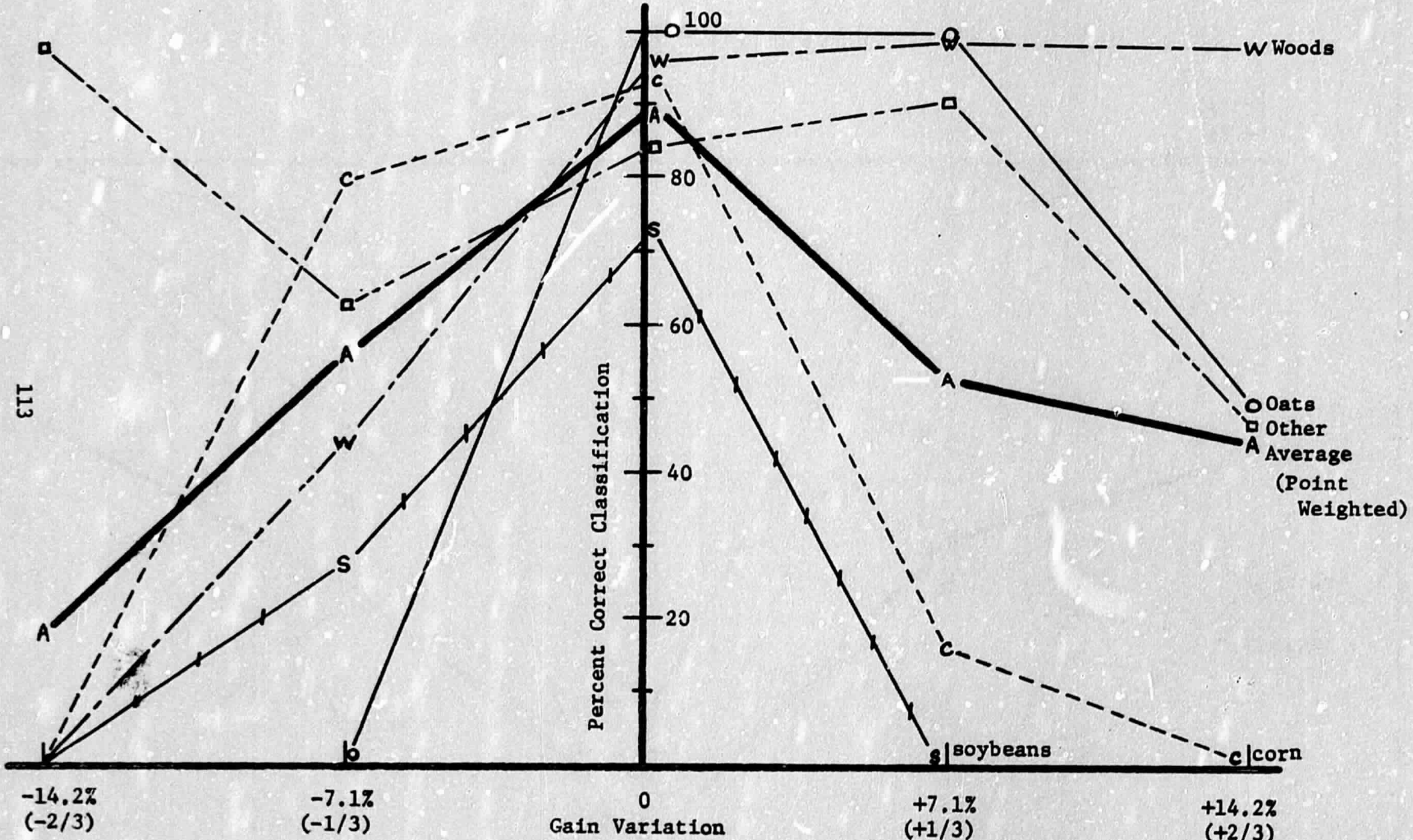


FIGURE 4-5. GAIN VARIATION EFFECTS ON MICHIGAN AGRICULTURE CLASSIFICATION RESULTS

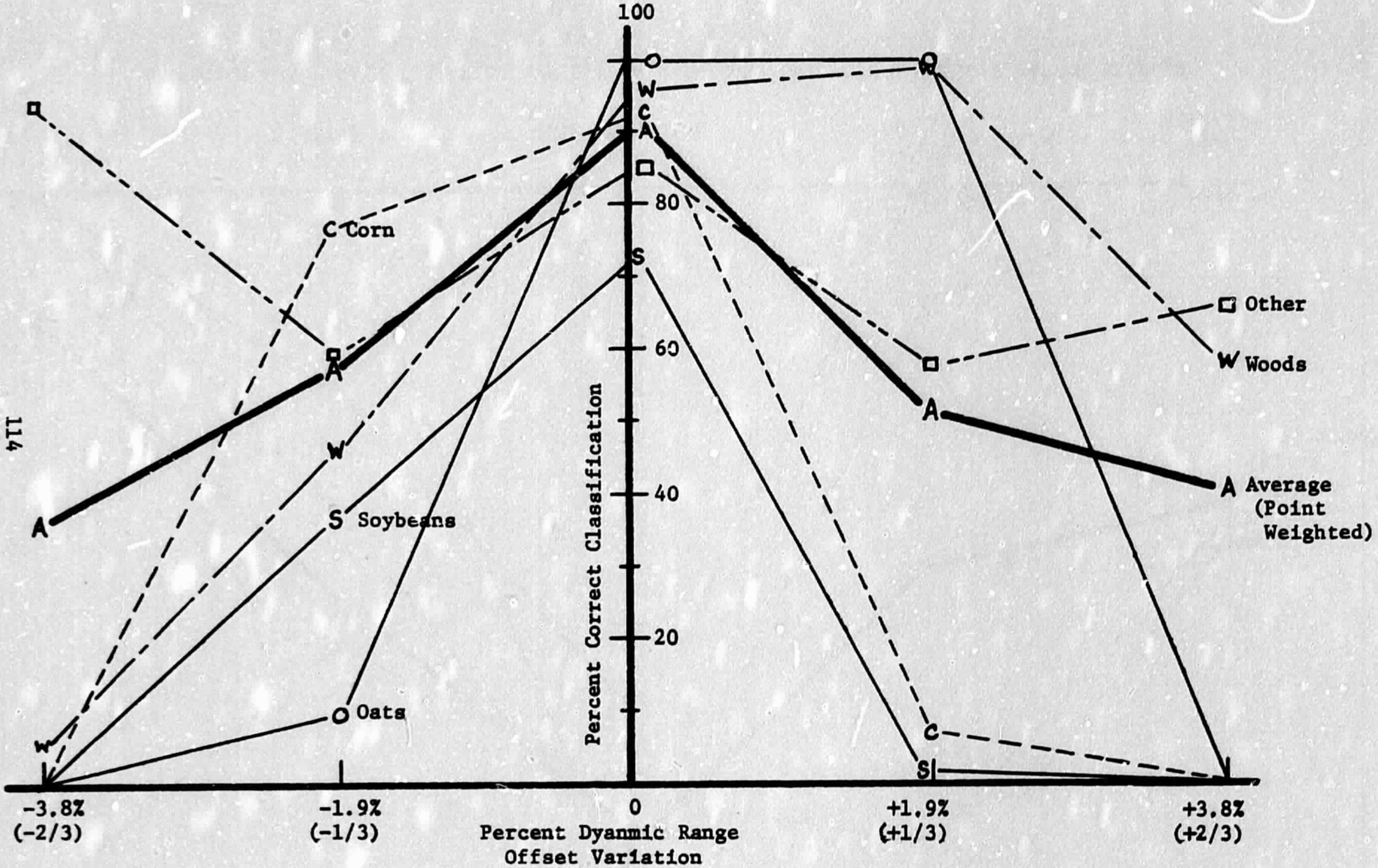


FIGURE 4-6. OFFSET VARIATION EFFECTS ON MICHIGAN AGRICULTURE CLASSIFICATION RESULTS

all the points are not classified whereas at ± 1/3 gain or offset a sizeable number of points are misclassified rather than not classified. This behavior seems intuitively correct. As gain or offset vary, the first effects noticed will be misclassification. As more extreme variations are encountered, no classification decision at all will be made because the signatures and data differ by such great amounts that the χ^2 test is not satisfied.

Qualitatively, the same remarks that were made for the Baltimore data apply to the agriculture data of Figures 4-5 and 4-6. The same general types of behavior occur although woods and "other" have an unexplained anomalous behavior.

The implications for system design of these results fall mainly in the areas of system calibration stability, inter-detector calibration within a spectral band, and in the implementation of radiometric corrections for changing solar illumination and for varying atmospheric transmission and path radiance effects. These corrections will be important in applications such as agriculture which require survey of large areas. Over these large areas, the solar elevation angle and atmospheric state are likely to vary considerably. Approaches for taking these illumination and atmospheric effects into account in preprocessing or adaptive classifiers have been studied at ERIM.

4.4 DISCUSSION OF RADIOMETRIC REQUIREMENTS FOR WATER QUALITY MAPPING

One of the most important water resources and marine resource study requirements is the mapping of water quality. Of the many variables affecting water quality we will deal here with chlorophyll content and suspended solids concentration. Because of the absorbing properties of the chlorophyll molecules and the scattering properties of the suspended sediments, choice of spectral bands is important. Water transmission and the fact that suspended sediments and chlorophyll often occur together make the spectral band choice a compromise, and

the precision in these bands is expected to be high because of the low water reflectance.

To extract chlorophyll concentration and suspended solids information from multispectral scanner data, ratios of two bands are commonly used. Using field measurements coupled with theoretical calculations, both the form of the relationship between chlorophyll and suspended sediments and the reflectance ratio and the constants required for calculation can be deduced. Wezernak at ERIM presented a paper at the Ninth Symposium on Remote Sensing of Environment[1] describing such relationships.

From those equations, relationships can be derived between the NE$\Delta\rho$ of the sensors and the equivalent chlorophyll and suspended solids measurement precision.

Table 4-4 lists the equations Wezernak derived for chlorophyll concentration and for water transparency depth, a parameter related to suspended solids required to calculate NE$\Delta\rho$.

We calculated two cases for transparency and chlorophyll — an oceanic and a coastal case. The values assumed for each case are shown in Table 4-5.

The values of reflectance are reasonable ones for the concentration and transparency conditions considered.

Figures 4-7 and 4-8 show the results of the calculations for chlorophyll and transparency. Chlorophyll accuracy for a given NE$\Delta\rho$ is best in the oceanic case where concentrations are low, provided that a sensor can be built to achieve these NE$\Delta\rho$'s at the low radiances typically found over deep oceanic water. For the coastal case, the precision is poorer in absolute terms, but the concentration of chlorophyll is higher. The reflectance of water may also be somewhat

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[1]Use of Remote Sensing in Limnological Studies, C. T. Wezernak, Ninth Symposium on Remote Sensing of Environment, in publication.

TABLE 4-4. WEZERNAK EQUATIONS FOR CHLOROPHYLL AND TURBIDITY

$$\log \text{Transparency depth (m)} = -0.6235 + 0.8788 \quad \frac{\rho(0.5\text{-}0.54)}{\rho(0.62\text{-}0.70)}$$

$$\log \text{Chlorophyll (mg/m}^3) = -2.4761 + 5.5668 \quad \frac{\rho(0.62\text{-}0.70)}{\rho(0.42\text{-}0.48)}$$

To calculate the effect of NE$\Delta\rho$ on these computations, we derived the equations shown below.

$$\Delta T = 1.247\ T_o\ \Delta\rho \quad \frac{\rho_1+\rho_2}{\rho_1\ \rho_2}$$

$$\Delta CH = 4.9522\ CH_o\ \Delta\rho \quad \frac{\rho_1+\rho_2}{\rho_1\ \rho_2}$$

where T_o, CH_o = reference transparency and chlorophyll levels

$\Delta\rho$ = NE$\Delta\rho$ of both channels (assumed equal)

ρ_1,ρ_2 = reflectances in the two bands.

TABLE 4-5. PARAMETERS ASSUMED FOR CALCULATIONS

Oceanic Case

$1\ mg/m^3$ chlorophyll

$\rho_1 = 2.0\%$

$\rho_2 = 0.4\%$

20m Transparency

$\rho_1 = 4\%$

$\rho_2 = 0.5\%$

Coastal Case

$10\ mg/m^3$ chlorophyll

$\rho_1 = 2.4\%$

$\rho_2 = 0.5\%$

10m Transparency

$\rho_1 = 10\%$

$\rho_2 = 3\%$

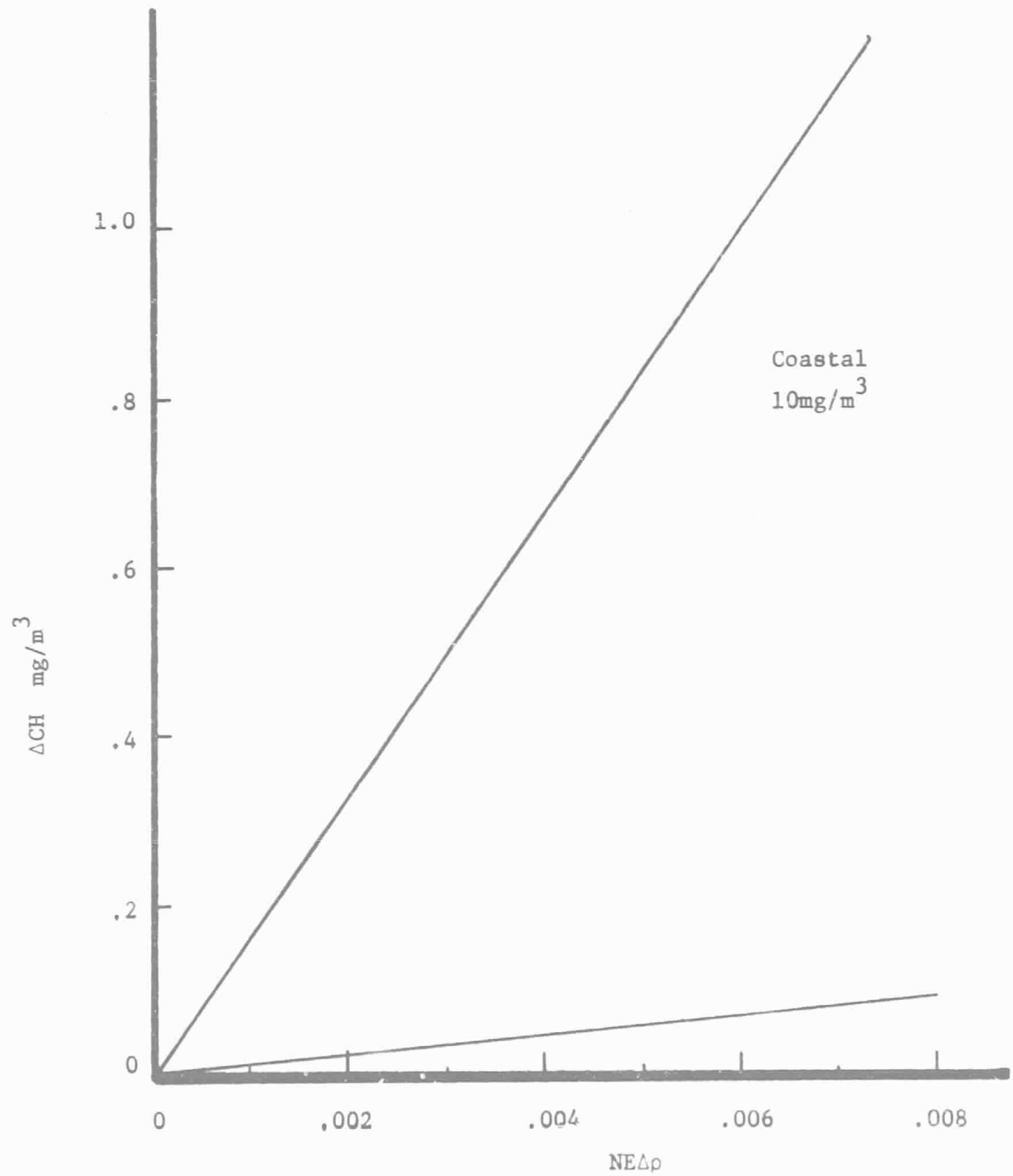

FIGURE 4-7. EFFECT OF NEΔρ ON CHLOROPHYLL CONCENTRATION CALCULATIONS

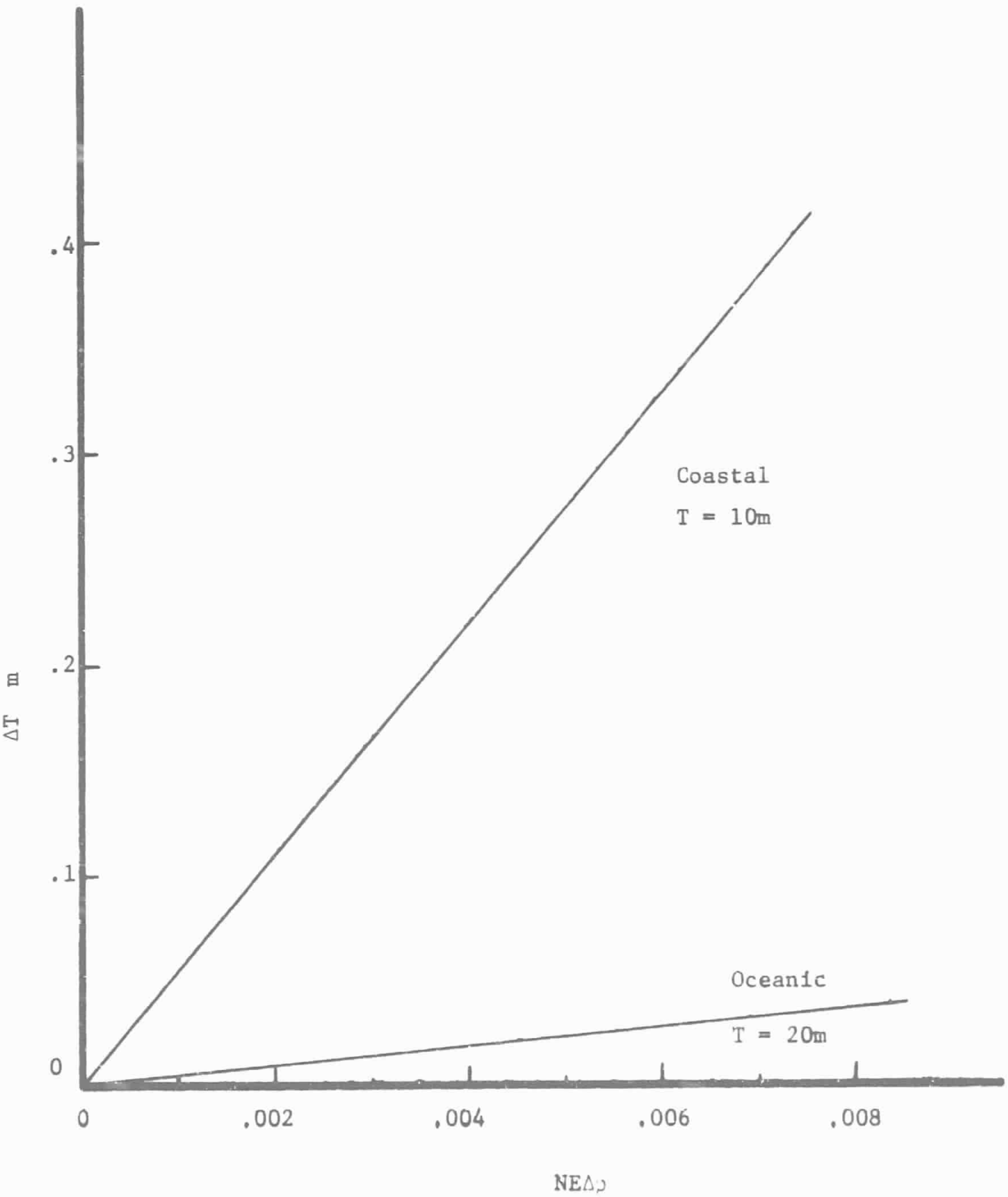

FIGURE 4-8. EFFECT OF NEΔρ ON TRANSPARENCY CALCULATIONS

higher. For a given level of NE$\Delta\rho$ of 0.007 in both channels, these calculations indicate a 10 percent precision measurement of chlorophyll in both oceanic and coastal cases can be made.

For the transparency results, the same comments may be made. Fluctuations in transparency in oceans may be so small that the 0.1 m precision obtainable at 0.007 NE$\Delta\rho$ may be unacceptably large. In the coastal case (also typical of some of the inland lakes) good precision of transparency measurement at 0.007 NE$\Delta\rho$ is indicated by these calculations. Noise in the data would cause fluctuations of 0.4 m on a typical 10 m transparency estimate.

As a footnote to these calculations, Wezernak has used ERTS data to map suspended solids in the Detroit River outfall into Lake Erie. He found by slicing the red band (with a quoted NE$\Delta\rho$ of about .95%) that sediment concentration of 3 mg/ℓ could be measured. This is more than a factor of 3 from the desired level of precision. Thus this application may require a 0.007 NE$\Delta\rho$ if the stated user requirements are to be met totally with a satellite system. But useful sediment mapping could be done with systems of lower radiometric precision.

4.5 THEORETICAL EXAMINATION OF RADIOMETRIC REQUIREMENTS FOR WATER DEPTH MAPPING

Mapping depths of water in coastal areas is one of the important water resources or marine tasks. Many shoal areas are poorly charted and are in remote areas such as the South Pacific and Southern Caribbean Sea.

Using multispectral scanner data, water depth has traditionally been measured by one of two techniques. Either a density slice of a band in the blue-green or green has been made, or a ratio of bands has been sliced. The latter technique has the advantage of being relatively less sensitive to bottom composition. Both techniques depend on being able to see the bottom and on the signal from the bottom increasing as water gets shallower.

Using the formula for calculating the water depth by the ratio technique, we developed an equation to compute the "noise equivalent water depth" given an equal NE$\Delta\rho$ in two spectral bands. Because the equation relating the water depth to reflectance is non-linear, the "noise equivalent water depth" will vary depending on the depth of the water. We calculated "noise equivalent depth" curves vs. NE$\Delta\rho$ for 3 and 5 m water depths. Other reasonable assumptions were made as shown in Table 4-6.

The results of calculations are shown in Figure 4-9. Notice that the measurement of depths at 5m with a precision greater than 5 m requires an NE$\Delta\rho$ of 0.0017 or better in both channels. At 3 m, an NE$\Delta\rho$ of about 1% (off the chart) yields a depth precision of 3 m and an NE$\Delta\rho$ of about 0.003 yields a depth precision of 1 m. The latter number is within a factor of 2 of ERTS performance. (Even though MSS-4 and MSS-5 are located slightly differently. The difference in absorption coefficient α was about the same.) The 1 m precision was about that obtained by Lyzenga and Polcyn in the Bahamas area using low gain ERTS data.

Calculations show what radiometric accuracy is required for given depth precision. The relatively stringent requirements on NE$\Delta\rho$ can probably be achieved at the expense of spatial resolution for the water depth case. A resolution of 30 m for such applications is probably too fine for the shoal reconnaissance mission required for satellite; 80 m might be more reasonable. Later aircraft surveys can more precisely chart and define the depths of shoals discovered by satellite. But to detect the 5 m deep water, and to distinguish it from deeper water, the calculations show that 0.002 NE$\Delta\rho$ is probably required.

4.6 CONCLUSIONS AND RECOMMENDATIONS - RADIOMETRIC STUDY

Tables 4-7 through 4-11 give the recommended NE$\Delta\rho$ or NEΔT for each spectral band for the five user discipline areas considered in the

TABLE 4-6. ASSUMPTIONS FOR WATER DEPTH CALCULATIONS

Bands .50 - .54 and .58 - .64

Water absorbtion coefficients (x) $0.27m^{-1}$ and $0.48m^{-1}$ respectively (mean coastal water)

Solar elevation angle 45° = θ

View angle 0° = ϕ

$$\Delta Z = 2 \quad \frac{\Delta\rho_1}{\rho_1} + \frac{\Delta\rho_2}{\rho_2}$$

$$Z = \frac{1}{(\alpha_1-\alpha_2)\ (\sec\theta+\sec\phi)} \quad \ln K \quad \frac{\rho_1}{\rho_2} \quad \frac{\rho_{B2}}{\rho_{B1}}$$

ρ_B = Bottom reflectance

Z = Depth

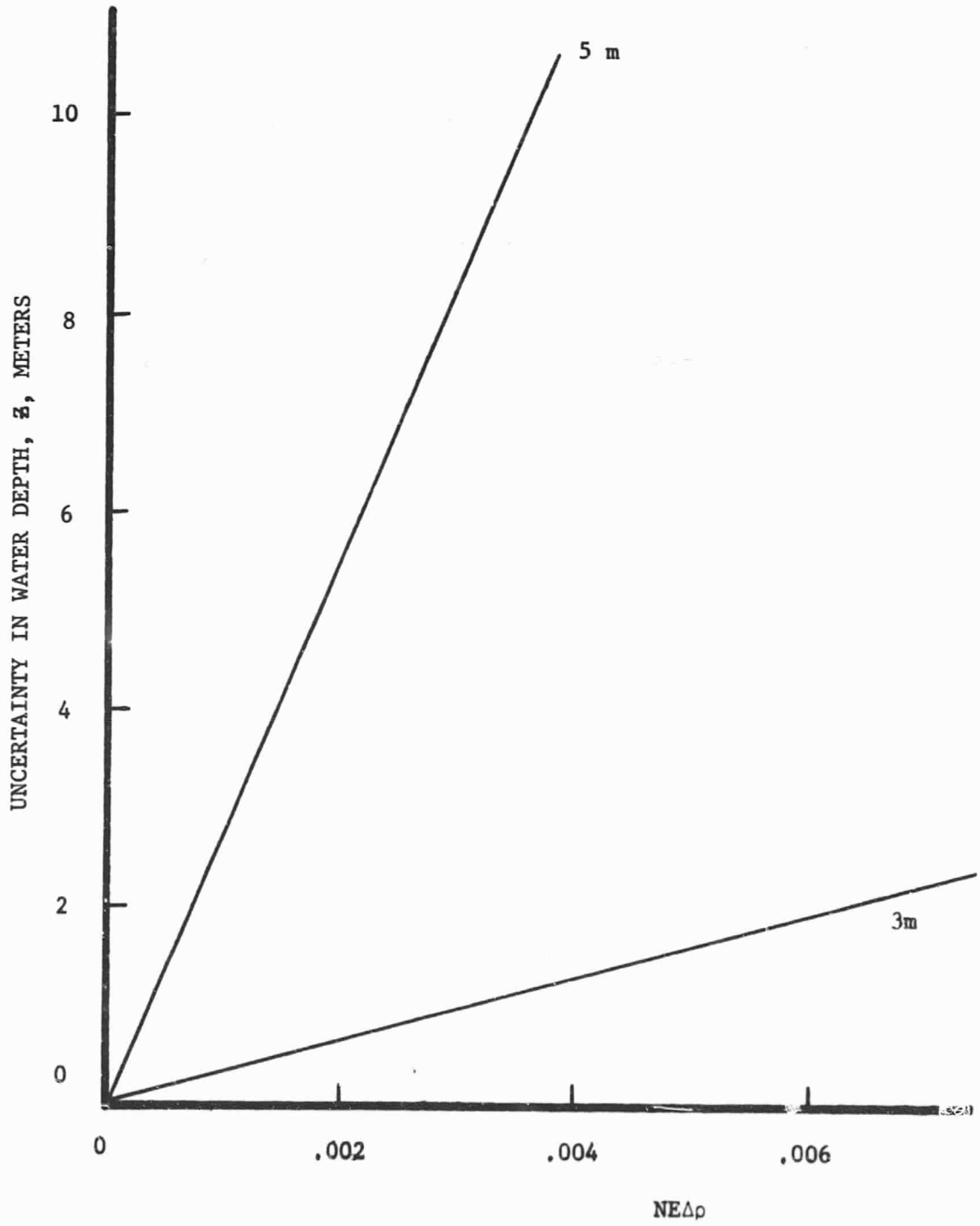

FIGURE 4-9. NEΔρ REQUIREMENTS FOR WATER DEPTH MAPPING 0.50-0.54 & 0.58-0.64 μm

TABLE 4-7. **RADIOMETRIC REQUIREMENTS**

Ag/Range/Forestry

BAND (μm)	T1/ρ1	T2/ρ2	NEΔT/NE$\Delta\rho$	MEASURED PARAMETER
0.55-0.60	0.05	0.20	0.005	Chlorophyll transmittance, absorption by other pigments
0.63-0.69	0.02	0.15	0.005	Chylorophyll-A absorbance
0.69-0.75	0.08	0.45	0.005	Slope between chlorophyll-A abs. and cell structure
0.75-0.95	0.15	0.60	0.005	NIR high reflectance (leaf cell structure)
1.55-1.75	0.20	0.45	0.005	Leaf moisture
2.05-2.35	0.15	0.30	0.005	Leaf moisture
10.4-12.5	270°K	313°K	1°K	Temperature

TABLE 4-8. RADIOMETRIC REQUIREMENTS

Geology

BAND (μm)	$T1/\rho 1$	$T2/\rho 2$	$NE\Delta T/NE\Delta\rho$	MEASURED PARAMETER
0.45-0.50	0.04	0.70	0.007	Fe absorption, carbonate
0.52-0.56	0.04	0.75	0.007	Strong green absorbance of rocks with iron oxide stain; increased reflectance of rocks containing minerals with ferrous iron
0.63-0.68	0.04	0.78	0.007	Strong red reflectance of rocks with iron-oxide stain
0.8-1.1	0.06	0.85	0.008	Fe absorption of both ferric and ferrous iron, copper sulfides
1.1-1.35	0.06	0.90	0.006	Soils
1.55-1.75	0.06	0.95	0.005	Aluminum oxide hydrate (gibbsite)
2.05-2.35	0.06	0.95	0.005	Carbonate molecular vibration absorption (OH) in clay minerals for soil identification
8.3-9.3	250°K	340°K	1°K	(1) thermal inertia (2) changes in the ratio of these two indicating migration of restrahlen (SiO_2 emittance)
10.5-12.5	250°K	340°K	1°K	

TABLE 4-9. **RADIOMETRIC REQUIREMENTS**

Water Resources

BAND (μm)	T1/ρ1	T2/ρ2	NEΔT/NE$\Delta\rho$	MEASURED PARAMETER
0.32-0.38				Fish oils and petroleum
0.42-0.48	0.02	0.10	0.005 0.002	Chlorophyll-A absorption
0.48-0.52	0.02	0.15	0.005 0.002	Chlorophyll-A absorption, suspended solids, turbidity, transparency
0.5-0.54	0.02	0.20	0.005 0.002	Water depth, suspended solids
0.52-0.58	0.02	0.20	0.005 0.002	Water depth, turbidity, trnsparency, suspended solids
0.58-0.64	0.02	0.20	0.005 0.002	Red tide (red algae)
0.62-0.68	0.02	0.15	0.005 0.002	Chlorophyll-A absorption, sediments
0.69-0.74	0.02	0.15	0.005 0.002	Algae bloom near surface
0.8-1.1	0.02	0.20	1.0 0.5	Land-water interface
10.4-12.5	270°K	305°K	0.5°K 0.25°K	Temperature

TABLE 4-10. **RADIOMETRIC REQUIREMENTS**

Marine/Oceanography

BAND (μm)	T1/ρ1	T2/ρ2	NEΔT/NE$\Delta\rho$	MEASURED PARAMETER
0.32-0.38				Fish oils and petroleum
0.42-0.48	0.02	0.10	0.001	Chlorophyll-A absorption
0.48-0.52	0.02	0.15	0.001	Chlorophyll-A absorption, suspended solids, turbidity, transparency
0.5-0.54	0.02	0.20	0.001	Water depth, suspended solids
0.[illegible]-0.58	0.02	0.20	0.001	Water depth, turbidity, transparency, suspended solids
0.[illegible]-0.64	0.02	0.20	0.001	Red tide (red algae)
0.62-0.68	0.02	0.15	0.001	Chlorophyll-A absorption sediments
0.69-0.74	0.02	0.15	0.001	Algae blooms near surface
0.8-1.1	0.02	0.20	0.5	Land-water interface
10.4-12.5	270^{o}K	305^{o}K	0.5^{o}K	Temperature

TABLE 4-11. **RADIOMETRIC REQUIREMENTS**

Urban Land Use

BAND (μm)	$T1/\rho 1$	$T2/\rho 2$	$NE\Delta T/NE\Delta\rho$	MEASURED PARAMETER
0.42-0.48	0.05	0.25	0.005	Asphalt-concrete-grass vs. vegetation
0.5-0.54	0.03	0.20	0.008	Asphalt-concrete-bare soil vs. grass and trees
0.58-0.64	0.03	0.30	0.010	Albedo
0.63-0.69	0.02	0.25	0.010	Vegetation-albedo (chlorophyll-A, absorption)
0.8-1.1	0.03	0.60	0.010	Vegetation-albedo-water (leaf scattering)
2 - 2.6	0.03	0.40	0.010	Asphalt-concrete-bare soil vs. grass-trees
10.4-12.5	260°K	313°K	0.5°K	Temperature
				NOTE: These data are based upon preliminary empirical results of Baltimore/Washington S-192 and ancillary data processing only.

study. The columns T1/ρ1 and T2/ρ2 are the minimum temperature or reflectance and maximum temperature or reflectance respectively. The remarks in the measured parameter column list the primary phenomena of interest for that spectral band. Table 4-12 lists the achieved NE$\Delta\rho$ for S192.

These tables require some discussion. The stated requirement for 0.5% NE$\Delta\rho$ in Agriculture and Water Resources is based mainly on experience and the study results. The Agriculture NE$\Delta\rho/\Delta T$ is based on the empirical results of the noise simulation and from past experience. The Water Resources NE$\Delta\rho/\Delta T$ is based on the theoretical study and ERTS experience. The Geology NE$\Delta\rho/\Delta T$ is based on experience with ERTS. The Marine Resources NE$\Delta\rho/\Delta T$ comes from theoretical considerations and ERTS experience but can be met by spatial averaging as this application needs only coarse spatial resolution. The Land Use NE$\Delta\rho/\Delta T$ is based on the empirical study and experience.

The dynamic range should be considered and held to 256 if possible so as to allow an 8-bit data value with linear encoding. Comparison of the maximum radiance value expected with the noise equivalent radiance NEL yields the dynamic range. For .005 NE$\Delta\rho$ in the 0.62-0.68 μm band we expect an NEL of .047 for an L_{max} of 20.3. This gives a dynamic range of 431. This indicates a 9-bit data value unless some type of automatic gain control is used. But it is not expected this will prove difficult to accommodate in the design.

A result with which we have some experience is also confirmed by Chang[2], namely, agricultural applications and many spectral bands from which to choose. Some noisy bands can be tolerated if the choices of optimum bands will still provide the discrimination between classes to enable classification accuracy on test areas better than 90%.

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[2] C. Y. Chang, "Skylab S192 Data Evaluation: Comparisons with ERTS-1 Results," LEC-1711, JSC, Houston, January 1974.

TABLE 4-12. NE$\Delta\rho$ (ΔT) FOR S192

WAVELENGTH	BAND	SL2 NE$\Delta\rho/\Delta$T	SL3 NE$\Delta\rho/\Delta$T
.41 - .46	1	1.3	1.3
.46 - .51	2	1.0	1.1
.52 - .56	3	1.3	1.2
.56 - .61	4	2.8	2.8
.62 - .67	5	3.1	2.5
.68 - .76	6	1.5	1.5
.78 - .88	7	1.8	1.7
.98 - 1.03	8	1.5	1.5
1.09 - 1.19	9	0.9	1.2
1.20 - 1.30	10	1.9	1.7
1.55 - 1.75	11	1.6	1.8
2.10 - 2.35	12	2.0	1.5
10.2 - 12.5	13	2.5°K	2.6°K

Some additional comments should be noted. There is an atmospheric phenomenon sometimes referred to as the "green haze" effect[3] in which the received radiance from a ground resolution element takes on or is contaminated by the spectral characteristics of surrounding objects not in the receiver's instantaneous field of view (IFOV). The primary component of this nontarget radiation is being reflected by objects outside the IFOV and is being scattered by the intervening atmosphere into the receiver. This path radiance effect, if large, could in some cases of coastal zone or water resources applications near highly reflective terrain provide a limiting noise effect. Radiative transfer model calculations for the atmosphere by Turner at ERIM are being pursued to estimate the magnitude of the effect under various conditions. Other atmospheric effects, such as scintillation due to turbulence, are also being calculated to determine if they are second order effects of some consequence.

[3]R. F. Nalepka, et al., "Investigations of Multispectral Sensing of Crops," University of Michigan Willow Run Laboratories, Report 31650-30-T, May 1971.

5
SPATIAL RESOLUTION STUDY

5.1 GENERAL

One of the more difficult problems in establishing user application requirements, and subsequently sensor design, is that of defining the spatial resolution required for a given application. With insufficient spatial resolution, objects of interest to the user will not be resolved and the necessary information will not be available. On the other hand, systems providing excessive spatial resolution, impose serious requirements on the design of the data acquisition, telemetry, and data processing systems. Also, the additional amount of data generated by the excessive spatial resolution increases the time and cost of data processing. Clearly then, an accurate definition of required spatial resolution is required. This section addresses this problem both from a theoretical and empirical viewpoint for Agriculture and Land Use.

5.2 SPATIAL RESOLUTION EFFECTS ON ACREAGE ESTIMATION

Section 5.2.1 discusses the effects of spatial resolution on agricultural field centers (portions of fields excluding all boundaries) as determined from the classification of aircraft scanner data. A discussion is then presented of the effects of spatial resolution on acreage estimation when the boundaries are included. Typical field sizes in various U. S. agricultural communities are presented and the results of acreage estimation on a set of fields in the aircraft data are provided and discussed.

5.2.1 SPATIAL RESOLUTION EFFECTS WITHIN FIELDS

Aircraft multispectral scanner data gathered over the Michigan agricultural test site were used to empirically determine the

effect of spatial resolution on classification accuracy. These data were processed to generate three separate digital tapes, each containing data for the scene at one of three spatial resolutions (nominal values of 15, 30, and 60 meters).

Utilizing the full 9-bit data, each of the data sets was classified with the optimum seven channels specified for each. The results of these classifications for field center pixels in test fields are shown in Tables 5-1, 5-2, and 5-3 for 15, 30, and 60 meter, respectively. The field center pixels for this aspect of the investigation are those pixels which were identified to fall within the boundaries of the test fields. A very conservative selection of field center pixels was made to insure that the selected pixels would not cross field boundaries at any of the three spatial resolutions. In fact, the selection was based on the 60 meter resolution data and the pixels selected for the 30 meter and 15 meter data sets were only those which were combined to generate the selected 60 meter pixels. As a result, the same ground area was covered in each field at each spatial resolution.

Table 5-1 shows that, with the exception of soybeans, the percent correction classification exceeds 80 percent. In fact, three of the classes (corn, ripe oats, and woods) exhibited accuracies exceeding 94 percent. As seen in Tables 5-2 and 5-3 which are for 30 and 60 meters, the same comments apply.

Some of the information included in Tables 5-1, 5-2, and 5-3 is depicted graphically in Figure 5-1. In this figure classification accuracy is plotted for each class as a function of spatial resolution. Also included is a plot of the weighted average of the individual results with the weighting being dependent on the number of pixels in each of the classes. On examining Figure 5-1, two major characteristics are obvious: 1) the percent correct classification for field center pixels for corn, ripe oats, woods, and "other" is either

TABLE 5-1. PERFORMANCE RESULTS
MICHIGAN AGRICULTURE TEST SITE

15 Meter Data
7 Optimum Channels
9 Bit Data

SCENE CLASS (No. of Pixels)	PER CENT CORRECT CLASSIFICATION	PER CENT MISCLASSIFICATION				
		CORN	SOY-BEANS	RIPE OATS	WOODS	OTHER
CORN (3248)	94.6		0.1		0.8	4.5
SOYBEANS (1136)	59.9	14.3				25.8
RIPE OATS (80)	100.0					
WOODS (3400)	95.5	2.8	0.1			1.6
OTHER (4672)	80.6	11.0	0.5	2.1	5.5	

Average = 86.1

Wt. Average = 86.5

TABLE 5-2. PERFORMANCE RESULTS
MICHIGAN AGRICULTURE TEST SITE

30 Meter Data
7 Optimum Channels
9 Bit Data

SCENE CLASS (No. of Pixels)	PER CENT CORRECT CLASSIFICATION	PER CENT MISCLASSIFICATION				
		CORN	SOY-BEANS	RIPE OATS	WOODS	OTHER
CORN (812)	94.1				0.7	5.2
SOYBEANS (284)	73.9	5.3				20.8
RIPE OATS (20)	100.0					
WOODS (860)	96.7	1.9				1.4
OTHER (1168)	84.8	9.5	0.4	1.0	4.2	

Average = 89.9

Wt. Average = 89.6

TABLE 5-3. PERFORMANCE RESULTS
MICHIGAN AGRICULTURE TEST SITE

60 Meter Data
7 Optimum Channels
9 Bit Data

SCENE CLASS (No. of Pixels)	PER CENT CORRECT CLASSIFICATION	PER CENT MISCLASSIFICATION				
		CORN	SOY-BEANS	RIPE OATS	WOODS	OTHER
CORN (812)	93.6		0.5		0.5	5.4
SOYBEANS (284)	29.6	29.6				40.9
RIPE OATS (20)	100.0					
WOODS (860)	97.7	1.9				0.4
OTHER (1168)	87.0	8.6		2.7	1.6	

Average = 81.6

Wt. Average = 85.7

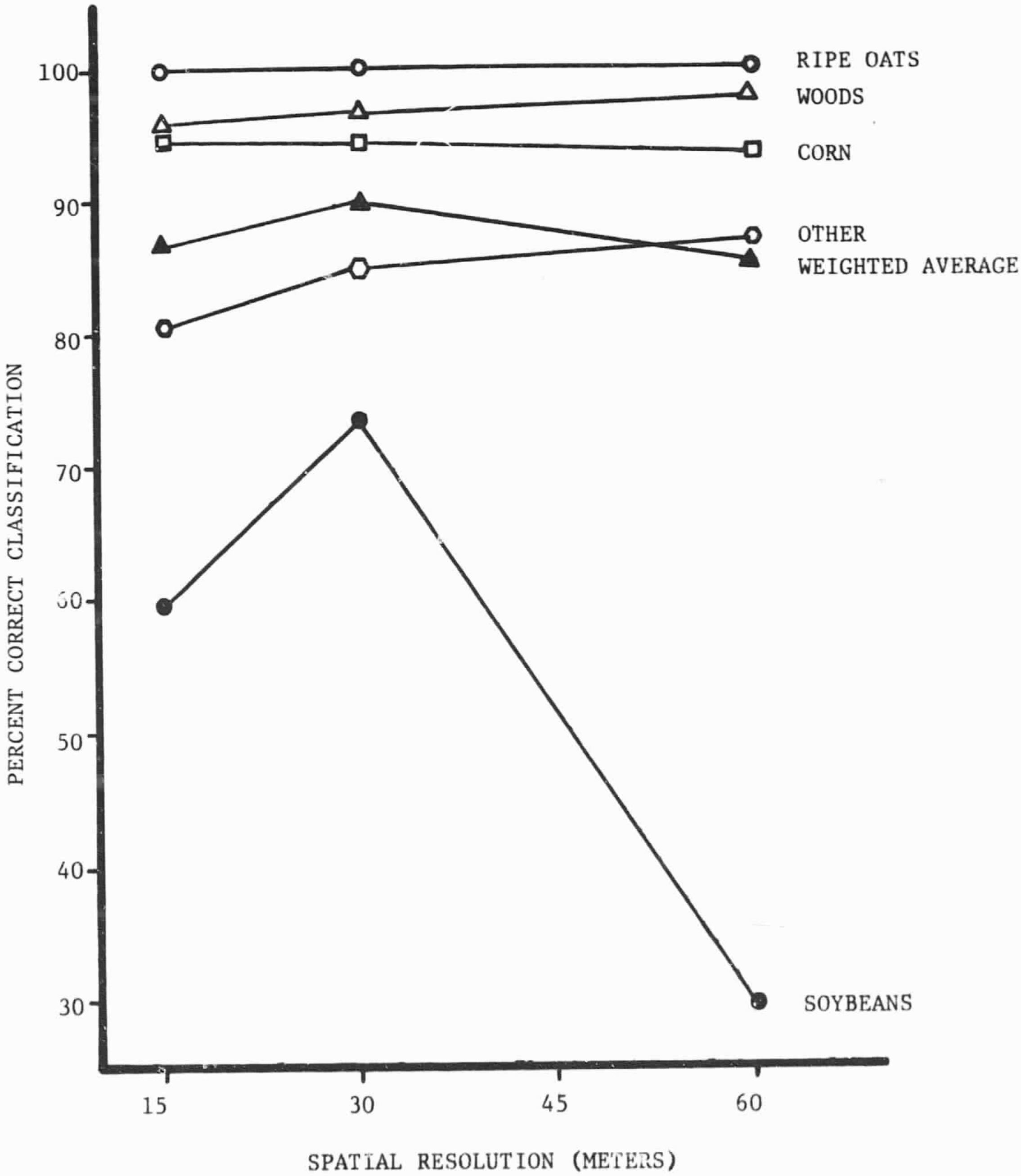

FIGURE 5-1. CLASSIFICATION ACCURACY AS A FUNCTION OF SPATIAL RESOLUTION FOR AGRICULTURE (FIELD CENTERS ONLY)

essentially flat or increases slightly with a coarsening of spatial resolution and 2) the percent correct classification for soybean field center pixels increases dramatically between 15 and 30 meters and decreases even more dramatically between 30 and 60 meters.

On examining the results for soybeans, in some detail, possible explanations for the action between 15 and 30 meters were determined (see Appendix B), however within the time and funding limitations of this investigation no reasonable explanations were determined for the reduction in classification accuracy between 30 and 60 meters. The result depicted here for soybeans is considered atypical and should not be used to select the optimum spatial resolution for the EOS sensor.

On the other hand, the results for the remaining classes (corn, ripe oats, woods, and "other") can be reasonably explained. For corn and ripe oats there is essentially no change in the classification accuracy with coarsening resolution. The test fields for the classes were relatively uniform in appearance and contained no regular structure at or near the spatial resolution being considered. This was not the case for woods and "other", however. Test fields for these classes were relatively nonuniform and, therefore, as the effective spatial resolution was reduced an increasing number of these nonuniformities were included within single pixels with the result that the variability from pixel to pixel was reduced and the classification accuracy increases slightly.

In summary, it has been demonstrated that, for agricultural field center pixels, a selection of a specific spatial resolution between 15 and 60 meters is not critical. In fact, for field center pixels, there is a slight preference for the coarse spatial resolution (60 meters in this case).

5.2.2 WHOLE FIELD ACREAGE ESTIMATION (THEORETICAL)

In the previous discussion our attention was intentionally limited to field center pixels. It is obvious, however, that those pixels which are located so as to overlap the boundary of adjoining fields need also be considered when specifying the required system spatial resolution. As a matter of fact, on an intuitive basis, it is the boundary pixels which will contribute most to errors in acreage estimation since each boundary pixel contains within it (by definition) portions of two or more fields which may be different crops. The radiation received from such pixels is a mixture from two or more classes and may, therefore, not be characteristic of either or any of the classes. The result of this mixture is likely to be that many of the boundary pixels will be incorrectly classified and the resulting field acreage estimate will be in error.

The following paragraphs present a simple theoretical approach to quantify the magnitude of this acreage estimate error and present the results of calculations of field acreage accuracy versus field size for a selection of spatial resolutions.

In order to mathematically model the situation at hand, some simplifying assumptions were made. The geometry shown in Figure 5-2 was assumed for modeling. A rectangular field is shown having dimensions A and B and pixels having dimensions "a" and "b" which are parallel to their opposite members. The equations for calculating the number of center and boundary pixels are shown below.

Number of pixels =

$$\left(\frac{A}{a}\downarrow -1\right)\left(\frac{B}{b}\downarrow -1\right)$$

where A,B are field dimensions and a,b are pixel dimensions.

$\frac{A}{a}\downarrow$ is the quotient of A and a rounded to the next lowest integer.

If a=b, aspect ratios of fields do not influence acreage accuracy vs. pixel size.

Boundary Elements $= \left(\frac{A}{a}\downarrow + \frac{B}{b}\downarrow + 2\right)$

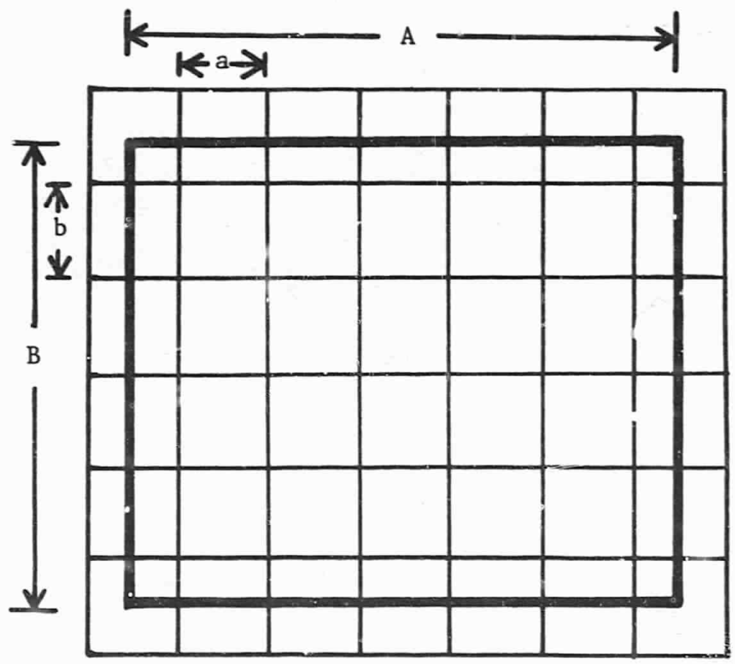

FIGURE 5-2. MODELING GEOMETRY

Using the above equations the number of center and boundary pixels and associated acreage were calculated for spatial resolutions of 10, 30, 60, and 80 meters for fields ranging in size from 5 to 2560 acres. These results are presented in Tables 5-4 through 5-7.

If two extreme situations are now considered: 1) all pixels, center as well as boundary, are classified as belonging to the class contained within the field and 2) all boundary pixels are classified as belonging to a class other than that within the field while all field center pixels are correctly classified, the range of possible values of field acreage accuracy can be determined. Such calculations were carried out using the data contained in Tables 5-4 through 5-7 and the results are depicted in graphical form in Figures 5-3 through 5-6.

On examining these figures it is clear the acreage overestimates occur for condition (1) and under-estimates occur for condition (2). As the field size is reduced for a given spatial resolution, the range of possible values increases significantly. This is especially true for spatial resolutions 30 meters or larger. Therefore, even though classification of some boundary pixels will match that of the field in practice, the uncertainties in acreage estimation accuracies will increase with decreasing field size and spatial resolution. This is shown more clearly in Figure 5-7 where we plot the maximum fractional error versus spatial resolution for various field sizes. Note that it is assumed in deriving these results that all field center pixels are perfectly classified. This may not be true in practice.

The potential seriousness of boundary pixel misclassification can be understood if one determines the average field sizes in many agricultural areas and then refers to Figure 5-7. Table 5-8 is a tabulation of field sizes and their distributions which were extracted from Statistical Reporting Service records for Kansas, Missouri, South Dakota, and Idaho. Only in Kansas, with its large wheat fields, is the average field size large enough (109 acres) to expect relatively small

TABLE 5-4. FIELD CENTER AND BOUNDARY PIXELS

10 m RESOLUTION

pixel = 0.02471 acres = 32.81 ft on a side

Field Size (acres)	Center Pixels (acres)	Boundary Pixels (acres)
2560	2530	31.8
*1280	1257	23.9
640	625	15.9
* 320	310.3	12.0
160	154.2	8.01
* 80	76.1	6.03
40	37.6	4.05
* 20	18.3	3.06
10	8.92	2.08
* 5	4.23	1.58

*Fields with 2:1 aspect ratio

TABLE 5-5. FIELD CENTER AND BOUNDARY PIXELS

30 m RESOLUTION

pixel = .2224 acres = 98.425 ft on a side

Field Size (acres)	Center Pixels (acres)	Boundary Pixels (acres)
2560	2499	96.1
*1280	1226	72.1
640	601	48.0
* 320	289	36.0
160	139	24.0
* 80	66.7	18.23
40	32	12.0
* 20	13.3	9.34
10	5.56	6.0
* 5	2.22	4.89

*Fields with 2:1 aspect ratio

TABLE 5-6. FIELD CENTER AND BOUNDARY PIXELS

60 m RESOLUTION

pixel = .8896 acres = 196.25 ft on a side

Field Size (acres)	Center Pixels (acres)	Boundary Pixels (acres)
2560	2405	192.2
*1280	1156	144
640	556	96.1
* 320	267	72.9
160	128	49.8
* 80	53.4	37.4
40	22.2	24.9
* 20	8.9	19.6
10	3.56	14.2
* 5	0	10.7

*Fields with 2:1 aspect ratio

TABLE 5-7. FIELD CENTER AND BOUNDARY PIXELS

80 m RESOLUTION

pixel = 1.581 acres = 262.47 ft on a side

Field Size (acres)	Center Pixels (acres)	Boundary Pixels (acres)
2560	2405	259
*1280	1172	196
640	571	132.8
* 320	270	101.2
160	128	69.6
* 80	56.9	53.8
40	25.3	37.9
* 20	6.32	28.5
10	1.58	19.0
* 5	0	15.8

*Fields with 2:1 aspect ratio

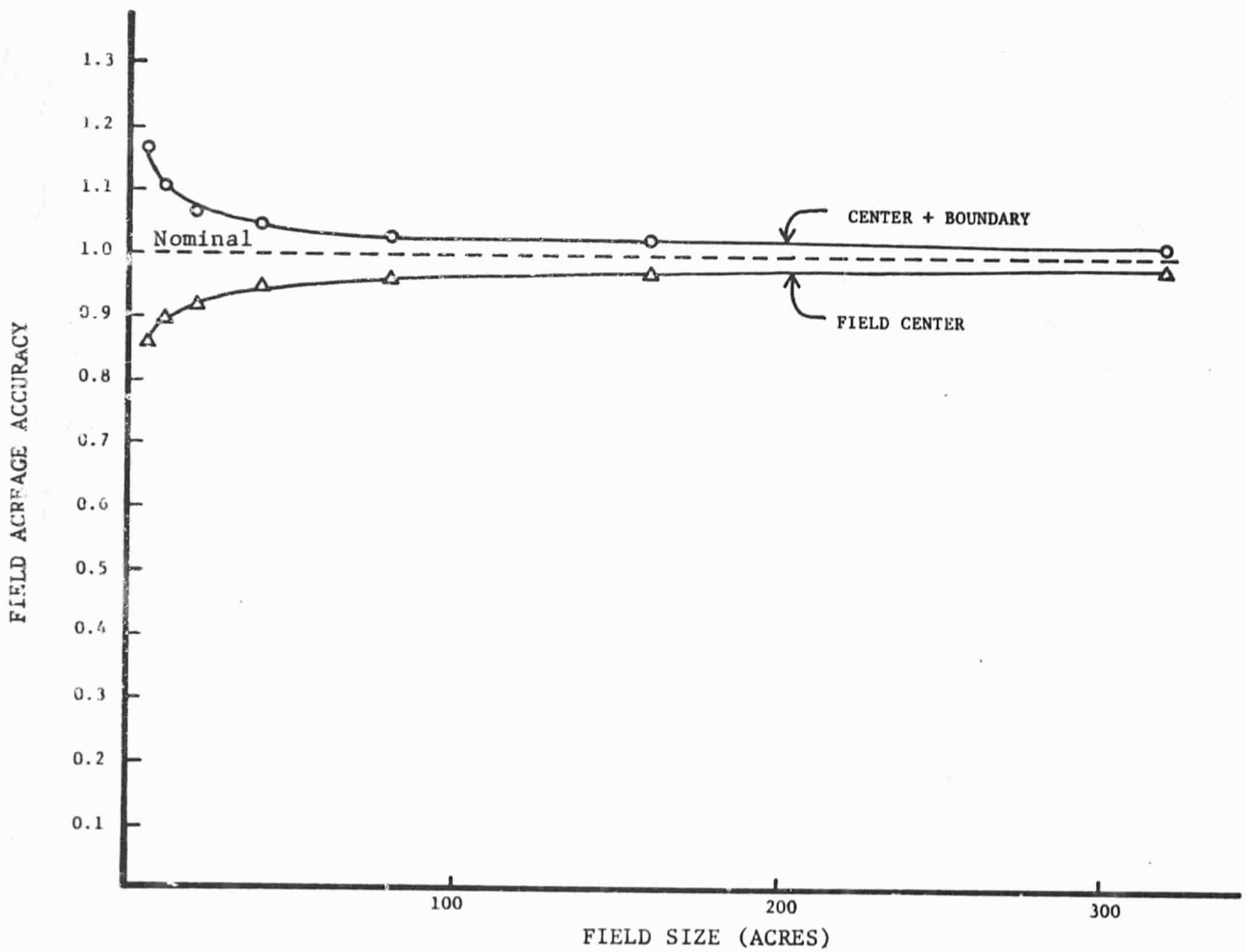

FIGURE 5-3. 10 METER RESOLUTION ACREAGE ACCURACY VERSUS FIELD SIZE

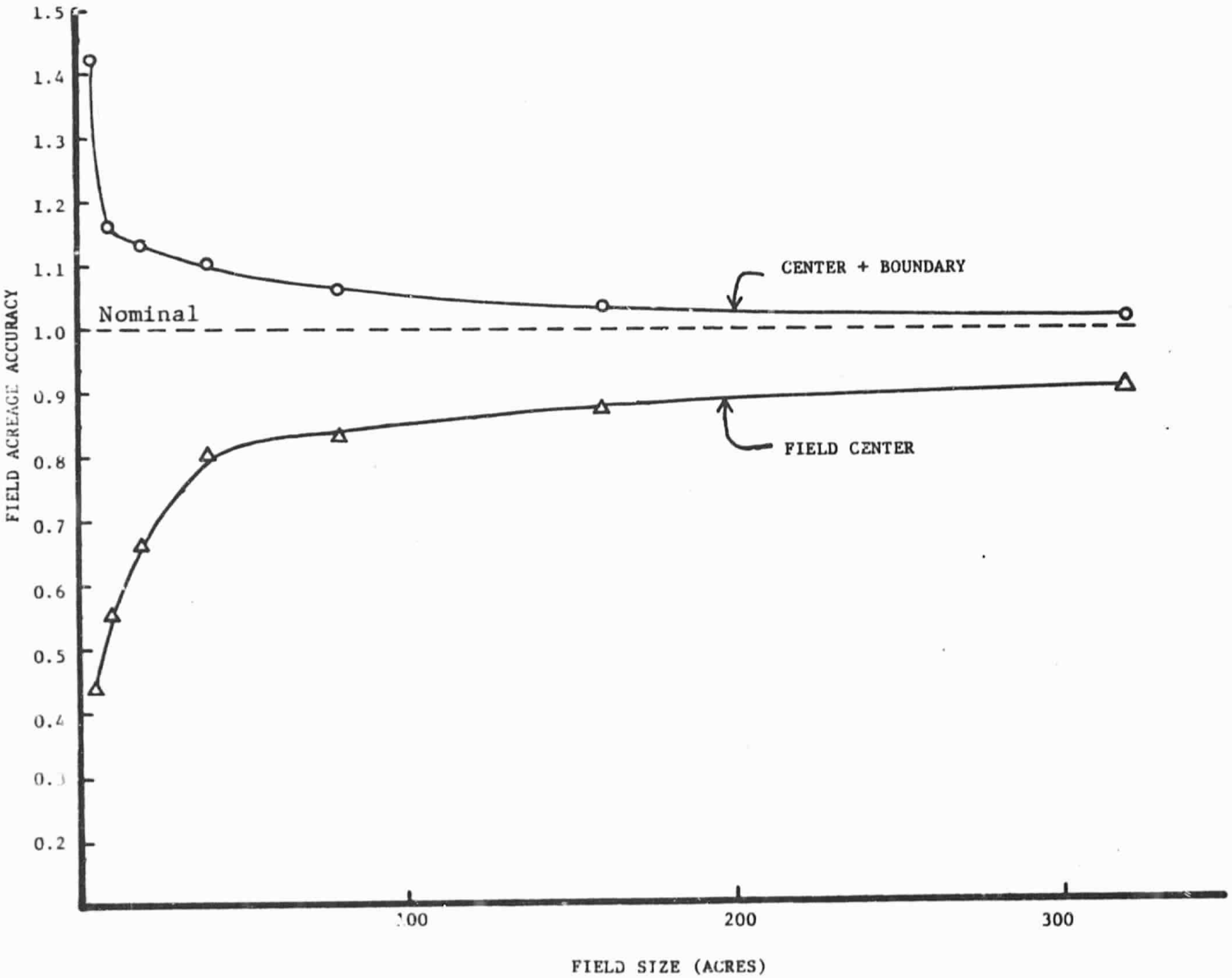

FIGURE 5-4. 30 METER RESOLUTION ACREAGE ACCURACY VERSUS FIELD SIZE

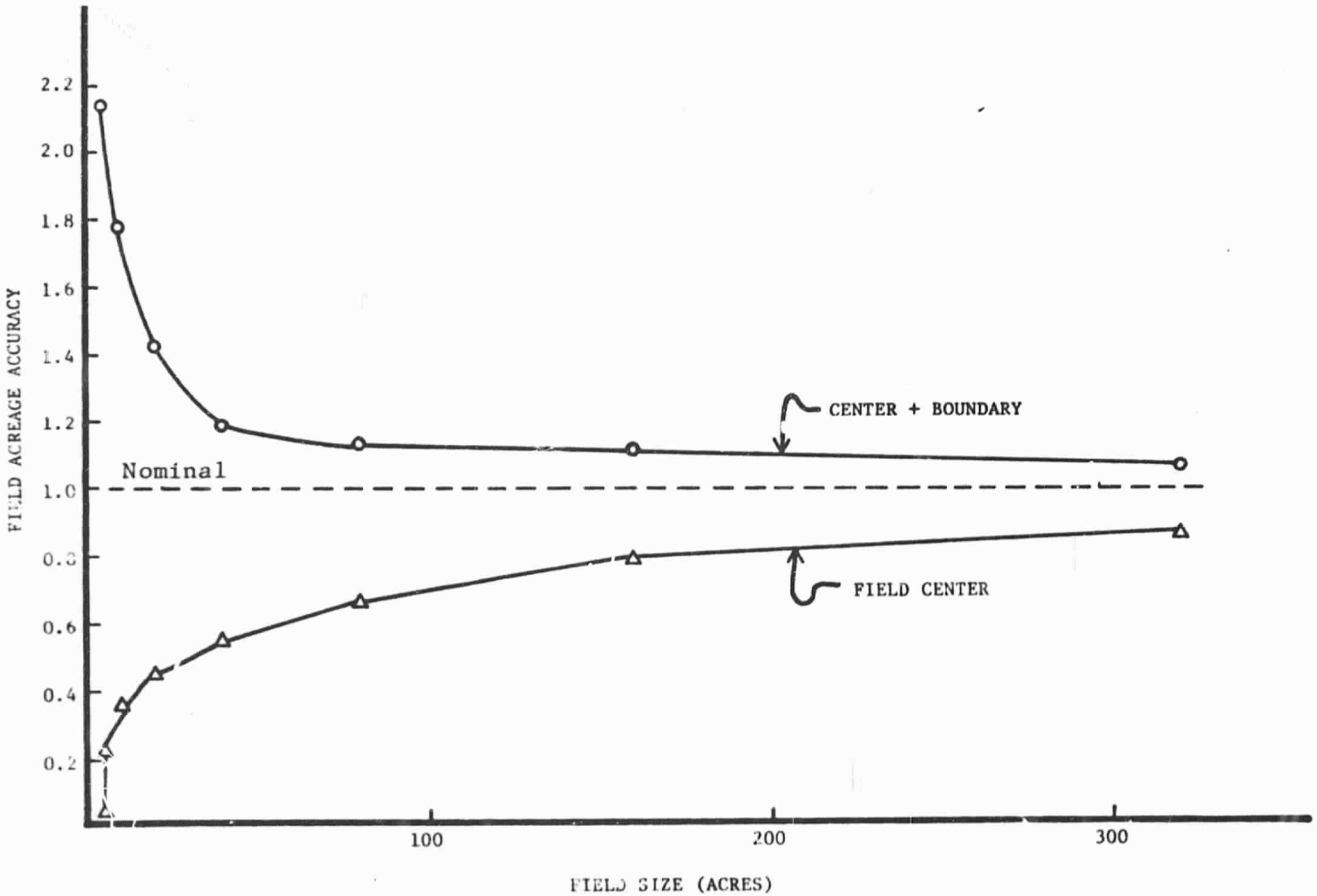

FIGURE 5-5. 60 METER RESOLUTION ACREAGE ACCURACY VERSUS FIELD SIZE

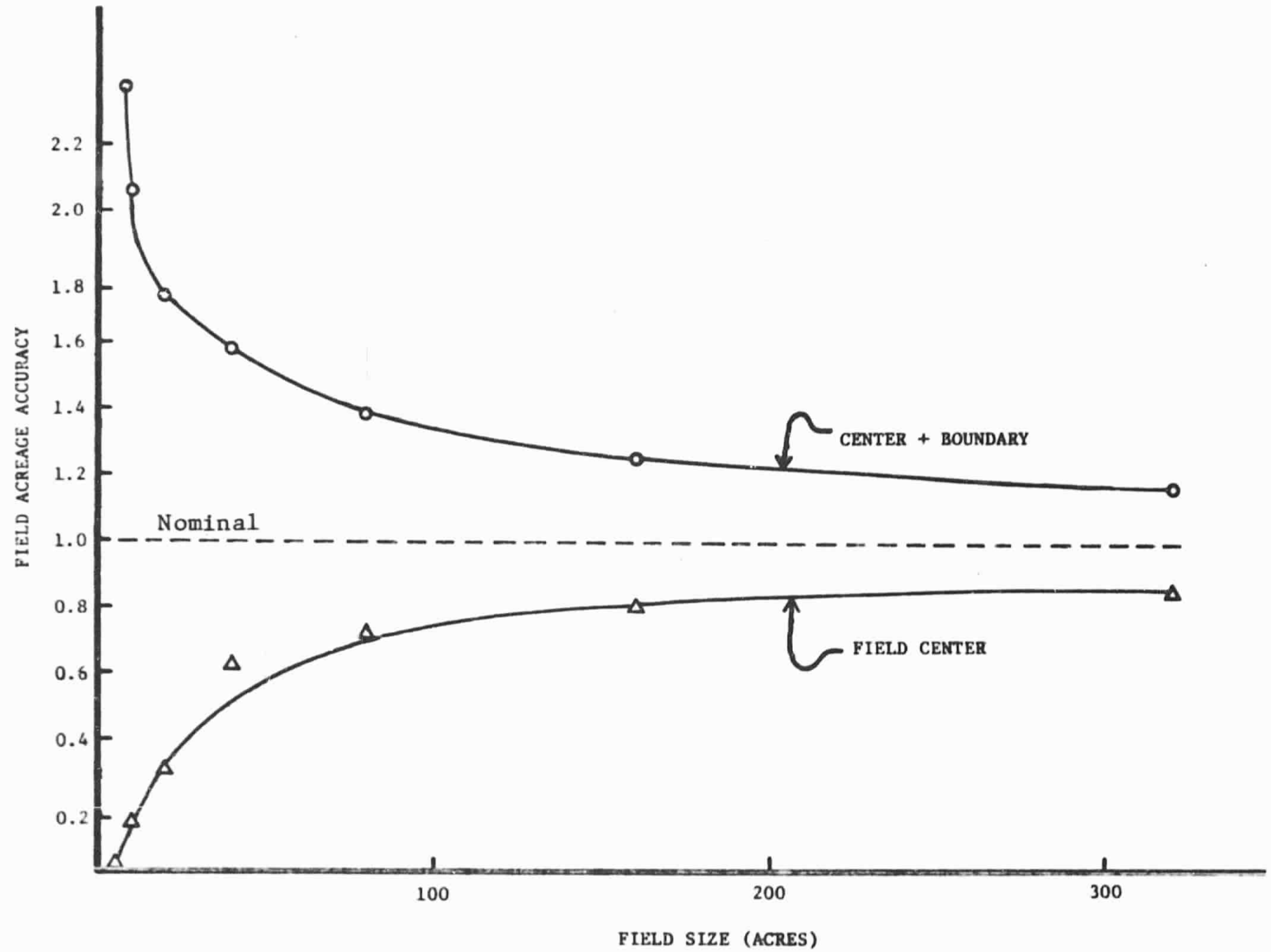

FIGURE 5-6. 80 METER RESOLUTION ACREAGE ACCURACY VERSUS FIELD SIZE

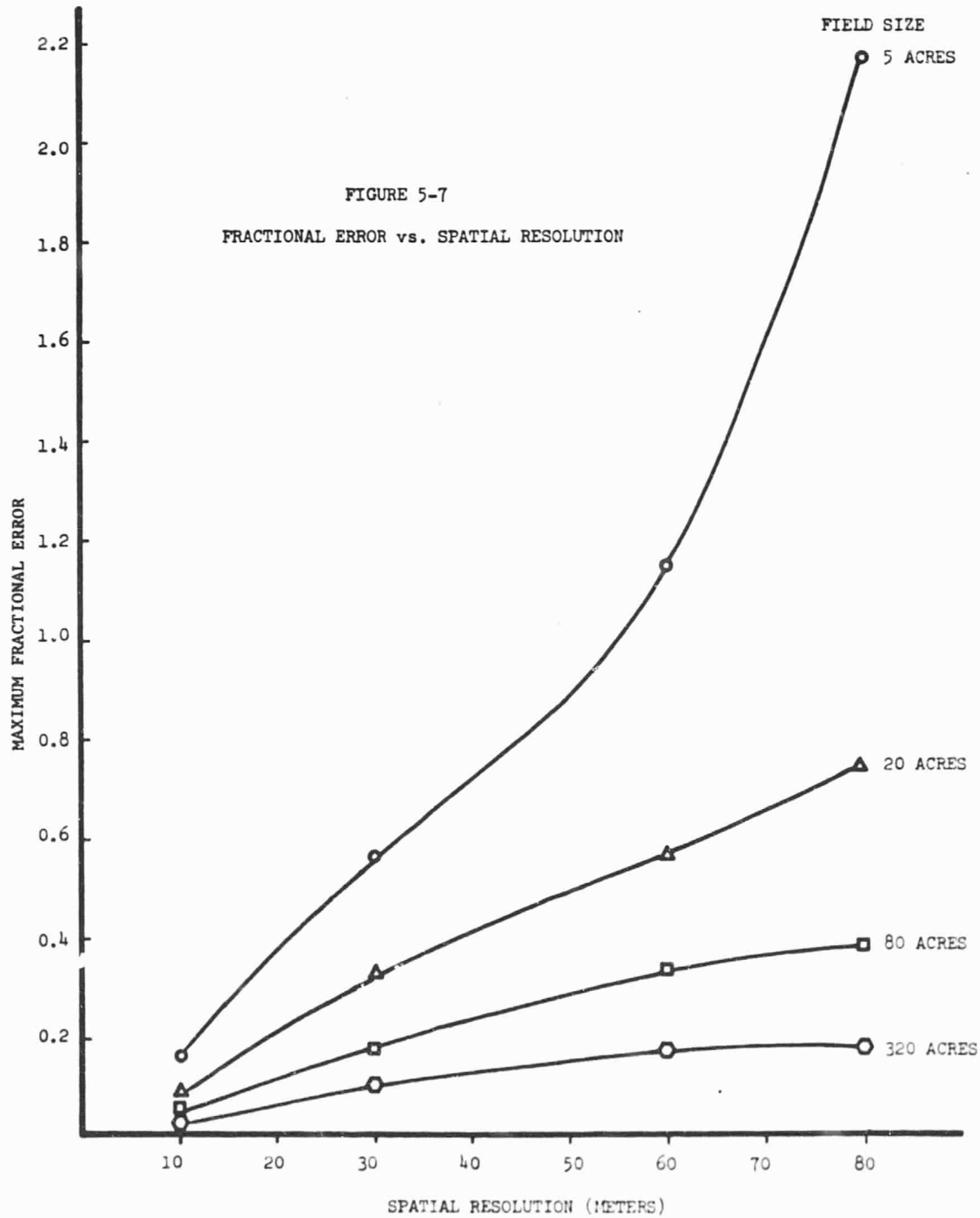

FIGURE 5-7. FRACTIONAL ERROR VERSUS SPATIAL RESOLUTION

TABLE 5-8 FIELD SIZE DISTRIBUTIONS

(Numbers in parenthesis are cumulative percentages)

Field Description	Test Site	Kansas		Missouri		South Dakota		Idaho	
0-9.9	#Fields	96		355		215		634	
	Acres	374.6		1,493.7		1,095.9		2,908.1	
	%Total	0.5	(0.5)	11.3	(11.3)	4.4	(4.4)	9.7	(9.7)
10.0-14.9	#Fields	29		123		108		211	
	Acres	316.5		1,415.1		1,231.6		2,483.0	
	%Total	0.4	(0.9)	10.7	(22.0)	5.0	(9.4)	8.3	(18.0)
15.0-19.9	#Fields	30		75		87		131	
	Acres	505.3		1,247.0		1,440.5		2,171.5	
	%Total	0.6	(1.5)	9.5	(31.5)	5.8	(15.2)	7.2	(25.2)
20.0-29.9	#Fields	52		98		165		130	
	Acres	1,248.1		2,276.8		3,842.6		3,118.1	
	%Total	1.5	(3.0)	17.2	(48.7)	15.5	(30.7)	10.3	(35.5)
30.0-39.9	#Fields	57		53		78		72	
	Acres	1,908.4		1,777.3		2,582.5		2,418.8	
	%Total	2.4	(5.4)	13.5	(62.2)	10.4	(41.1)	8.0	(43.5)
40.0-99.9	#Fields	234		60		175		123	
	Acres	14,919.9		2,375.4		10,245.7		7,507.8	
	%Total	18.3	(23.7)	25.6	(87.8)	41.4	(82.5)	25.0	(68.5)
100.0-499.9	#Fields	222		11		30		39	
	Acres	41,829.3		1,604.0		4,342.1		7,053.7	
	%Total	51.4	(75.1)	12.2	(100.0)	17.5	(100.0)	23.5	(92.0)
500.01	#Fields	25		0		0		3	
	Acres	20,215.0		0.0		0.0		2,409.3	
	%Total	24.9	(100.0)	0.0		0.0		8.0	(100.0)
TOTAL TEST SITE									
	#Fields	745		775		831		1,314	
	Acres	81,317.1		13,189.3		24,780.9		30,064.3	
Average Field Acreage		109		17		30		23	

maximum fractional acreage estimation errors as a result of spatial resolution greater than 30 meters. For the other three states listed, as well as the Corn Belt states of Illinois and Indiana for which some field size information is available, the maximum fractional acreage estimation error will fall in the 0.2 to 0.6 range for spatial resolutions of 30 and 60 meters.

5.2.3 WHOLE FIELD ACREAGE ESTIMATION (EMPIRICAL)

The question addressed in the previous paragraphs (acreage estimation errors) on theoretical grounds was also examined empirically using the aircraft multispectral scanner data gathered over the Michigan agricultural site. The procedure followed and the results achieved are described in the remainder of this section.

The processing of the agriculture data set was described in Section 2.2.1, which resulted in three classification maps, one each for 15, 30, and 60 meter spatial resolution data. A total of fifty fields of five types (bare soil, corn, soybeans, stubble, and hardwoods) were located on these maps. The region in the immediate vicinity of each of these fields was then examined to identify the number of pixels classified as the target field. The number of pixels were then transformed to field acreage. The results achieved in following this procedure are provided in Table 5-9 which lists the actual acreage as measured from aerial photography, along with the computer determined field acreage for each field. In this table the results are also broken out for each scene class according to five size classes (0-10, 10-20, 20-40, 40-80, and 80-160 acres).

The table shows that both underestimates and overestimates in field acreage occur, although underestimates predominate. In order to get a more general picture of these results, the absolute difference between the computer determined and actual field acreage was determined for each field. The results were combined according to

TABLE 5-9. AGRICULTURE SPATIAL STUDY - FIELD AREA AS A FUNCTION OF SPATIAL RESOLUTION

SCENE CLASS	SIZE CLASS (ACRES)	ACTUAL FIELD ACREAGE (AS MEASURED FROM PHOTOGRAPHY)	COMPUTER DETERMINED FIELD ACREAGE		
			15M DATA	30M DATA	60M DATA
Bare Soil	0-10	3.7	3.56	4.07	3.35
		4.3	3.08	3.47	4.86
		4.5	3.75	3.79	4.06
	10-20	18.3	13.40	13.90	11.39
		12.0	8.38	9.03	7.64
		14.0	13.47	13.59	13.27
	20-40	25.7	22.87	24.97	24.02
		31.7	30.49	29.09	30.05
		27.7	23.98	25.58	24.30
Corn	0-10	9.7	8.07	9.11	7.03
		8.0	4.73	3.82	3.47
		8.2	6.56	6.77	5.56
	10-20	23.0	16.42	14.39	13.43
		19.7	17.42	15.97	18.91
		14.3	12.27	12.56	7.37
	20-40	36.2	33.84	35.18	32.17
		21.3	19.53	14.70	14.07
	40-80	45.2	44.96	42.38	42.22
		76.8	75.53	75.45	77.37
		62.7	53.47	50.95	56.27
		77.2	78.41	76.96	26.22
	80-160	141.0	136.37	136.20	140.72
		153.2	147.39	141.57	141.74
Soybeans	10-20	11.5	9.47	10.76	8.47
		15.3	15.07	14.87	15.98
		17.2	15.19	15.51	17.90
	20-40	28.0	26.34	27.17	30.05
		32.2	26.47	26.24	27.38

TABLE 5-9 (Continued)

SCENE CLASS	SIZE CLASS (ACRES)	ACTUAL FIELD ACREAGE (AS MEASURED FROM PHOTOGRAPHY)	COMPUTER DETERMINED FIELD ACREAGE		
			15M DATA	30M DATA	60M DATA
Stubble (Cut Hay)	0-10	7.0 8.7 10.7	7.77 9.25 9.13	8.51 10.25 9.38	9.73 9.73 7.37
	10-20	11.5 19.5 18.8	13.65 17.21 14.66	13.07 16.42 13.40	12.73 18.09 9.38
	20-40	28.7 33.8	25.02 29.36	24.62 31.27	28.13 29.18
	40-80	49.3	44.69	45.07	43.56
Hardwoods	0-10	6.8 5.1 6.1	6.70 6.19 4.56	6.53 5.91 5.04	4.02 8.31 3.47
	10-20	15.3 9.7 10.6	12.31 10.27 10.86	12.71 10.39 11.38	9.78 9.67 8.85
	20-40	38.2 23.7 33.5	31.85 19.88 29.88	33.88 22.06 31.09	28.67 16.88 20.57
	40-80	67.2	58.59	59.98	55.62
	80-160	144.2	139.51	154.02	138.21

size class and spatial resolution and average absolute acreage estimation accuracy was determined. These results are tabulated in Table 5-10 and depicted graphically in Figure 5-8.

As expected, the acreage errors show a tendency to decrease with increasing field size and increasing (finer) spatial resolution, although the differences in the errors between 15 and 30 meters are small and variable. For smaller fields (those more commonly found) the average errors range from 11 to 20 percent for 15 and 30 meter resolution and from 20 to 38 percent for 60 meter resolution. According to these results it seems that there is a break point between 30 and 60 meter spatial resolution and that a resolution of 30 meters would clearly increase the accuracy while a further reduction to 15 meters would not change the results much.

In the above examples the boundaries of each of the fields on the classification maps were not located with extreme accuracy so it was felt that several examples where this was done would be interesting and perhaps further help identify the optimum spatial resolution for the EOS sensor.

The procedure followed here was to manually estimate the location of and draw the field boundary on the 15 meter resolution classification map. The drawn boundary was restricted to fall between pixels and therefore, because of the procedure, there were no boundary pixels on the 15 meter map. The boundary was then transferred to the 30 and 60 meter maps and boundary pixels (those through which the transferred boundary passed) and field center pixels were identified. Then using the area defined by the boundary on the 15 meter map, the accuracy of the effective area identified by the field center and boundary pixels was determined for the 30 and 60 meter resolution data.

The above procedure was applied to five fields ranging in size from 14 to 32 acres. The results are shown in Table 5-11 where we see that with the exception of the 14 acre field there seems to be no trend at all and that the absolute errors are fairly small, sometimes

TABLE 5-10. FIELD ESTIMATION ERRORS

NUMBER OF FIELDS	SIZE CLASS (ACRES)	AVERAGE ABSOLUTE ACREAGE ESTIMATION ERRORS		
		15-M	30-M	60-M
12	0-10	0.203	0.190	0.382
15	10-20	0.193	0.196	0.290
12	20-40	0.128	0.107	0.194
6	40-80	0.071	0.079	0.260
3	80-160	0.046	0.061	0.042

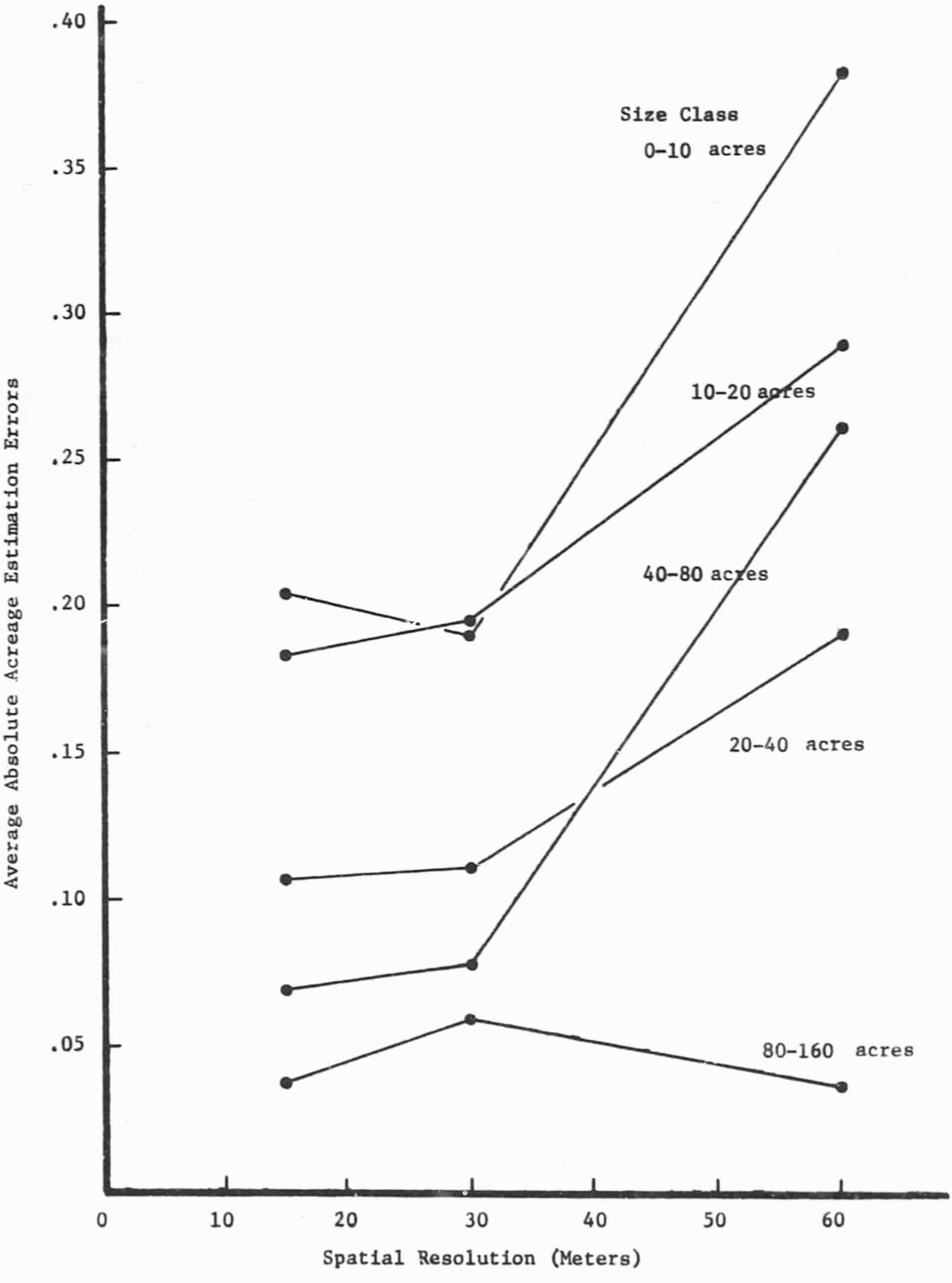

FIGURE 5-8. ACREAGE ESTIMATION ERRORS

TABLE 5-11. FIELD CENTER AND BOUNDARY ACREAGE ERRORS

FIELD SIZE (ACRES)	15 METER		30 METER		60 METER	
	FIELD CENTER	WHOLE FIELD	FIELD CENTER	WHOLE FIELD	FIELD CENTER	WHOLE FIELD
14	0.060	0.060	0.000	0.007	0.000	0.217
15	0.038	0.038	0.015	0.054	0.077	0.009
20	0.000	0.000	0.095	0.060	0.000	0.050
32	0.003	0.003	0.000	0.050	0.000	0.006
32	0.039	0.039	0.064	0.071	0.030	0.000

smaller for the whole field than for the field centers only. These results seem to indicate that boundary pixels are more or less randomly being classified according to the class of the target field with the result that there is little change in the accuracy of the acreage estimated.

There is some concern that these results may be unrepresentative because of the small size of the sample (only five fields) and the fact that each of the fields exhibited higher field center classification accuracy than was typical for this data set. Perhaps the procedure employed for this aspect of the investigation forced the selection of atypical cases. In any case, these questions were not examined because of limited study scope.

5.2.4 CONCLUSIONS AND RECOMMENDATIONS - AGRICULTURE SPATIAL

In this section the problem of defining the spatial resolution of a spaceborne multispectral scanner for Agriculture applications was addressed. The prime user application considered here was the determination of agricultural field acreage at three specific spatial resolutions (15, 30, and 60 meters).

It was demonstrated for the agricultural data set available for this study that the classification accuracy (and therefore, acreage estimate accuracy) for field center pixels is essentially not affected by a reduction in resolution from 15 to 60 meters. In fact, a slight improvement in accuracy was achieved for those classes which were less homogeneous and contained nonuniformities on the order of the final resolution.

When including boundary pixels, however, theoretical evidence pointed to continued reduction of acreage estimation accuracy with decreasing field size and coarser spatial resolution. Empirical results confirmed the reduction in accuracy with decreasing field size but indicated no reduction in accuracy in decreasing the spatial

resolution from 15 to 30 meters for fields as small as four acres.

Based on the empirical results presented in this section, a spatial resolution finer than 30 meters is not warranted. These results do support a case for a spatial resolution finer than 60 meters, but a precise resolution between 30 and 60 meters was not defined. It is suggested that studies such as these be made using data collected at more optimum times in the growing season in order to more clearly define resolution requirements.

Specific suggestions for the continuation of this study include the use of accurate boundary location techniques under development at ERIM to aid in the evaluation of boundary effects on classification accuracy and acreage estimation. In addition, larger areas in the scene for which there is complete ground information and which include many boundaries should be examined to determine whether errors of one kind in one location are compensated for by errors of another kind in another location. Also, there is a need to determine if there are fixed biases in acreage estimation and how these biases are affected by varying distributions in field size and type. Another area of investigation suggested to be pursued is the further development and testing of proportion estimation techniques which has been pioneered by ERIM. Such techniques permit the estimation of proportions of individual classes in pixels which contain more than one class. Perhaps an approach of this kind will in the future permit the use of coarser spatial resolution sensors with their attendant lower system electronics, telemetry, data acquisition, and processing costs while still retaining a capability for accurate area determination.

5.3 SPATIAL-SPECTRAL IDENTIFICATION STUDY URBAN LAND USE - BALTIMORE (HONEYWELL-MINNEAPOLIS)

The determination of the spatial resolution for an earth observing sensor must take into account the use of spatial information for object identification. Two aspects of spatial information are commonly used to discriminate between objects, texture and shape. These spatial features are commonly exploited by the photointerpreter. Since this study was oriented towards automatic identification of scene elements, spatial discriminants were added to the spectral features in the computer implemented identification routine. It was felt that spatial features were of great importance in the identification of urban land use, thus the selection of Baltimore as a test site. It was also expected that urban land use identification would be degraded with degrading spatial resolution. It seemed obvious at the study's inception that of all potential remote sensing applications, urban land use identification would be the most sensitive to changes in the spatial resolution of the sensor.

It is important to understand how spatial features were used in the study. The same scene was viewed with fundamental resolutions of 7, 14, and 56 meters. An 8 x 8 grid of surrounding resolution elements was associated with each 7 m resolution element. A 4 x 4 grid of surrounding resolution elements was associated with each 14 m resolution element. Thus, in each case, the grid covered 3136 m^2 of the scene. Each grid provides a small portion of the scene surrounding the resolution element. This scene grid provides the spatial data for the identification discriminant.

Figure 5-9 illustrates how a (4 x 4) rectangular scene element of intensity A surrounded by scene elements of intensity $\frac{A}{4}$ can be constructed from four texture patterns. The intensity of the shaded cells is $\frac{1}{2}$ and the clear areas 1. The number $\frac{1}{4}$ associated with each of the four texture patterns is called the <u>amplitude</u> of the pattern.

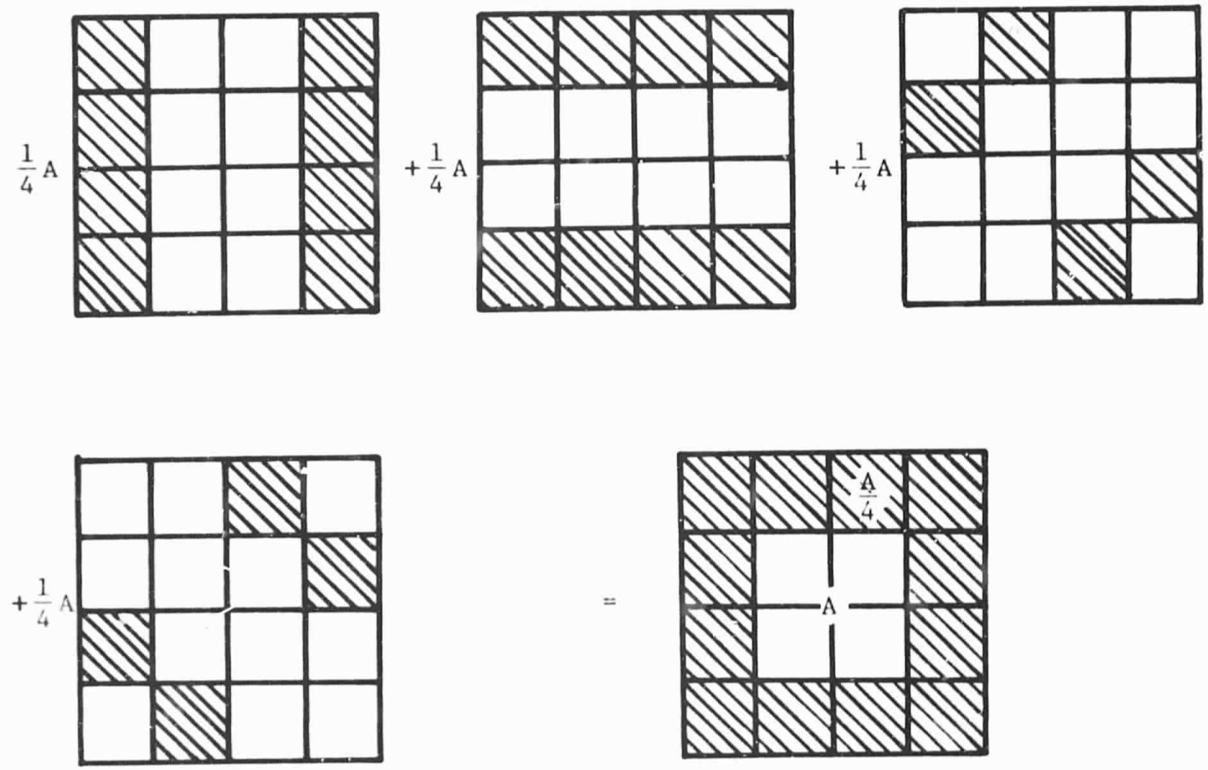

FIGURE 5-9. THE SCENE GRID AS THE SUM OF TEXTURE GRIDS

If each cell in the texture patterns of Figure 5-9 has side 14 m, then the first two texture patterns have a spatial frequency of 1 cycle/28 m, the last two a spatial frequency of $\sqrt{2}$ cycles/28 m.

The method used in this study for measuring the spatial features in the resolution element grids is similar to the method depicted in Figure 5-9. Each grid of resolution elements is expressed as a weighted sum of Fourier texture basis patterns. The weights are called amplitudes of the frequency of the Fourier basis pattern. Each Fourier basis pattern has a single spatial frequency associated with it.

Figure 5-10 shows the spatial frequencies produced by the 8 x 8 grid with cell side 7 m. The point (f_x, f_y) has the following interpretation: The Fourier frequency pattern is at an angle θ with the x-axis of the grid given by $\tan\theta = \frac{f_y}{f_x}$ and the frequency of the pattern is $\sqrt{f_x^2 + f_y}$. For example, the point (1,2) related to a periodic pattern oriented $\tan\theta = \frac{2}{1}$ or $\theta = 60°$ to the x-axis and has frequency $\sqrt{5}$ cycles/56 m, or 0.04 cy/m. The pattern (4, 4) has a spatial frequency $4\sqrt{2}$ cycles/56 m, or 0.1 cy/m. The amplitude associated with the Fourier spatial frequency pattern (f_x, f_y) is denoted by $A(f_x, f_y)$ and these amplitudes were computed by the Fast Fourier Transform technique from the resolution element amplitudes of the grid.

The values of the 8 x 8 and 4 x 4 resolution element grids were generated by the first principal component of the Karhunen-Loeve transformed spectral features. Both the maximum eigenvalue criterion and the Classifier Mapping Error (CME) criterion were examined for principal component selection to generate grid values. It turned out that selection of the principal component eigenvector associated with the maximum eigenvalue yielded the best classification accuracy. The need for rotationally-invariant, as well as translationally-invariant, features was recognized. The 2-D Fourier Transform was used to obtain an (N/2-1) x (N/2-1) matrix of "energy" values from an N x N cell. Rotation invariance was approximated for 8 x 8 and 4 x 4 cells by partitioning and combining Fourier spectral frequencies as described in Table 5-12.

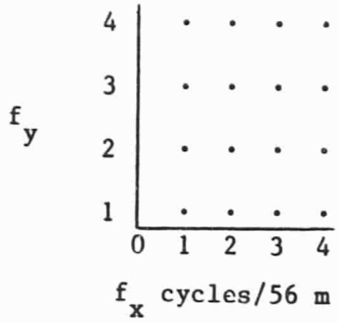

FIGURE 5-10. SPATIAL FREQUENCY LATTICE

TABLE 5-12. TEXTURAL FEATURE SPECIFICATION

<u>8 x 8 Grid</u>

Feature:

$$50 = A(0,0)$$

$$51 = A(1,0) + A(0,1) + 0.65\ A(1,1)$$

$$52 = A(2,0) + A(0,2) + 0.8[A(2,1) + A(1,2)] + 0.35\ A(1,1) + 0.1\ A(2,2)$$

$$53 = A(3,0) + A(0,3) + 0.9[A(3,1) + A(1,3) + A(2,2)] + 0.3[A(3,2) + A(2,3)] + 0.2[A(2,1) + A(1,2)]$$

$$54 = A(4,0) + A(0,4) + A(4,1) + A(1,4) + 0.35[A(4,2) + A(2,4)] + 0.7[A(3,2) + A(2,3)] + 0.1[A(3,1) + A(1,3)] + 0.8\ A(3,3)$$

$$55 = 0.65[A(4,2) + A(2,4)] + A(4,3) + A(3,4) + A(4,4) + 0.2\ A(3,3)$$

<u>4 x 4 Grid</u>

$$50 = A(0,0)$$

$$51 = A(0,1) + A(1,0) + 0.65\ A(1,1)$$

$$52 = A(0,2) + A(2,0) + A(1,2) + A(2,1) + A(2,2) + 0.35\ A(1,1)$$

The proportionality constants for combining Fourier spectral frequencies tabulated in Table 5-12 were selected empirically from studies performed upon transformations of rotated 8 x 8 patterns. The features are the weighted sum of the amplitudes of Fourier patterns of approximately the same frequency but in all the available directions. This is an approximation to rotational invariances.

The features 50-55 are amplitude representations similar to the amplitudes in a spectral channel. These spatial features are used in the classifier in the same way as are spectral features. Spectral-spatial signatures are obtained from training sets in the usual fashion. These spectral-spatial signatures are then used to classify the test sets. Honeywell uses a K-class linear discriminant as classifiers.

There are many methods for using spatial properties in a classifier. The Fourier technique is only one. Given a classification problem, we may expect to find one method preferred over another. Neither resources nor time allowed comparison of other techniques on this data. It is possible (but not likely) that the results presented would be radically changed by a change of technique. The Fourier technique is about as exhaustive as any available technique and it certainly should be responsive to the variations in the spatial resolution of the data. Another technique could no doubt improve classification results for each spatial resolution. It is doubted, however, that another classifier could change the relation of classification accuracy and resolution variation revealed by this study.

Ordering of Spatial-Spectral Channels

The classification exercise undertaken on the Baltimore data was the identification of 15 Anderson Level III classes given in Table 5-13. Three approaches to channel ordering were taken in this evaluation; forward, reverse, and exhaustive. In the forward evaluation, the best single channel is determined and the second best is added, then the third best is added to these two, etc., until all twelve channels have

TABLE 5-13. CLASS DESIGNATIONS FOR BALTIMORE DATA SETS

Description	Anderson Class	Honeywell Designation
Residential, Single Family	111	1
Residential, Multiple Family	112	2
Commercial, Retail	121	3
Industrial, Wholesale/Light Ind.	122	4
Industrial, Metal	132	5
Industrial, Chemical	134	6
Transportation, Railroads & Yards	152	7
Transportation, Freeways/Highways	153	8
Transportation, Marine Terminals	154	9
Transportation, Utilities	155	10
Institutional	160	11
Institutional, Secondary Schools	162	12
Institutional, Colleges	163	13
Institutional, Military Installations	164	13
Institutional, Other (e.g., Hospitals)	165	14
Open/Other (Urban Parks, Recreational)	190	15

been categorized. In the reverse evaluation, the least effective channel is deleted first, then a second least effective channel is added to this, etc., until all twelve have been categorized.

In the exhaustive search, the most effective channel is determined, then the two most effective are determined, the three most effective, etc., until all twelve have been analyzed. The difference here is that the n + 1 most effective need to contain all n of the n most effective; that is, selected channels can be deleted as the number of channels increases.

The ordering of channels selected by these three schemes is given in Table 5-14. A curve of mapping error for the exhaustive schemes is given in Figure 5-11.

Surprisingly, feature 51 is the only spatial feature ranked ahead of a spectral feature and all remaining spatial features and feature 51 has a basis frequency of one cycle per 56 m, the lowest frequency available. The highest frequency 4 cycles/56 m is ranked very low by both the forward and reverse methods. Figure 5-11 further strengthens this result. The spatial channels decrease the probability of misclassification by only a small amount. Results of the next section will further amplify this result.

<u>Effects on Classification Accuracy of Changes in Resolution</u>

The "working data" was extracted from the Baltimore flight using the provided graymap, scanner "photos" and ground truth map. About 2200 8 x 8 cells (56 m/side), belonging to the classes adequately represented, were selected, assigned a class number, and extracted from the original high-resolution data tape. Sometimes the Level III classification was further broken down when such a class was composed of obvious dissimilar "subgroups". This was to allow more flexibility and selectivity where necessary in subsequent processing.

Training and testing sets of data were defined among the extracted data. If a subgroup had $\geq$ 80 cells in it, every other cell of that

TABLE 5-14. CHANNEL ORDERING

Forward:	12	10	9	51	8	1	11	2	52	55	53	54	50
Reverse:	12	9	8	1	10	52	11	2	52	54	53	55	50
Exhaustive:	12												
	12	10											
	12	10	9										
	12	9	8	1									
	12	10	9	8	1								
	12	10	9	8	1	51							

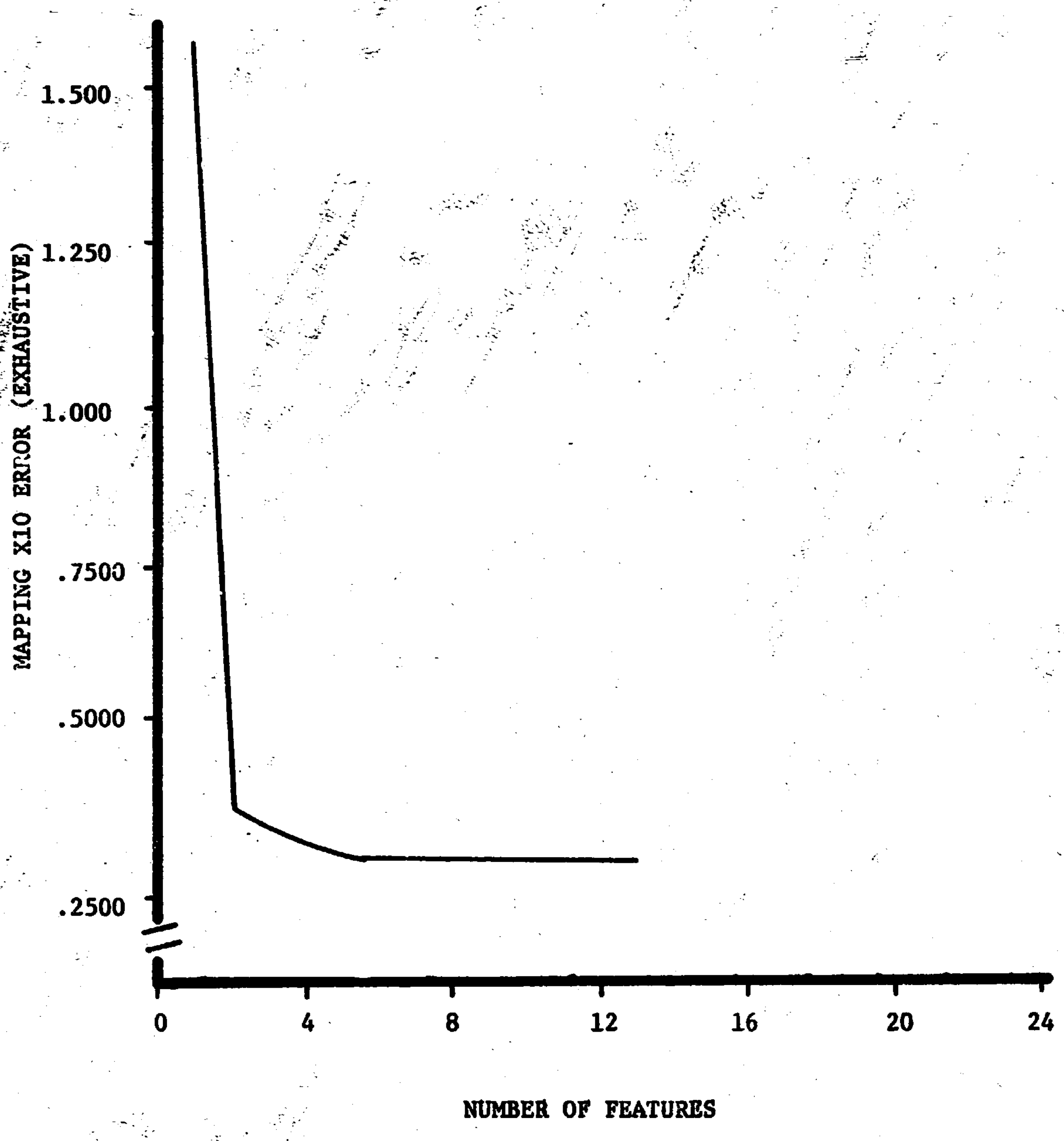

FIGURE 5-11. SPECTRAL-SPATIAL RANKING (7 m)

subgroup in sequence on the extracted data tape was assigned to the training set, and the remaining cells to the testing set. Where the population was < 80 cells, every cell was assigned to both sets. This assured an adequate statistical representation of every class in subsequent classifier processing. This is almost an experiment on training sets. The results are given in the form of performance matrices, Tables 5-15 to 5-26. The diagonal elements are the probability of correct classification for each class. The off diagonal entries are the probabilities of calling the i^{th} class (row #), the j^{th} class (column #). The "best" seven features are shown in Table 5-27. The twelve performance matrices represent the three resolution levels and the different spectral-spatial features used with each resolution. Table 5-28 is a summary of the weighted average of correct classification. Weights were determined by the number of resolution elements in each class.

It is apparent that at each resolution the addition of spatial information improves classification accuracy. Further comparing the accuracy for 4 spectral channels to 7 spectral channels plus all 6 of the available spatial features at 7 m resolution, results in an accuracy increase of 13 percent. At 14 m resolution comparing the 4 best spectral channels with the 7 best spectral channels plus all 3 available spatial features, an accuracy increase of 7.1 percent is realized. The addition of spatial features then, appears to have more impact at high resolution than low. But notice that the accuracy of spectral discrimination alone improves markedly with degraded resolution. Obviously, the integration of scene elements implicit in degraded resolution is reducing the spectral variability within the scene's classes and thus markedly improving the accuracy of the spectral discrimination. This integration effect is so strong that although the 7 m, 7 spectral channel, 6 spatial feature accuracy is slightly better than 14 m, 7 spectral channel, 3 spatial feature accuracy, the

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Table 5-15. Classification Percentages
7 Meter Cell, 2 Best Features*
(2 Spectral Bands)

TRUE CLASS \ CLASSIFICATION	1/	2/	3/	4/	5/	6/	7/	8/	9/	10/	11/	12/	13/	14/	15/
CLASS 1/	26.9	9.7	.0	2.0	.0	.8	.2	1.2	1.8	12.4	.9	9.5	25.6	3.3	5.6
CLASS 2/	9.7	8.5	.0	16.0	1.6	1.2	.0	.8	3.9	11.7	1.9	2.8	30.0	13.0	.0
CLASS 3/	4.7	6.6	.0	39.2	.9	1.3	3.3	.0	2.2	4.9	4.9	5.2	10.4	16.0	.8
CLASS 4/	3.3	8.9	.0	44.6	2.6	2.6	.9	.0	1.9	2.4	8.7	2.1	7.3	14.8	.0
CLASS 5/	.8	.2	.0	21.7	16.5	1.9	11.5	.0	11.5	2.3	16.7	15.5	1.0	.5	.0
CLASS 6/	6.7	4.3	.0	16.5	7.3	2.8	5.0	1.5	4.8	11.8	10.4	8.2	10.8	9.9	.1
CLASS 7/	1.4	1.4	.0	3.9	2.2	1.7	27.8	.0	.0	1.1	45.3	7.8	4.7	2.8	.0
CLASS 8/	9.6	11.1	.0	7.4	.0	2.7	.2	.0	.4	9.0	7.0	1.4	36.3	14.3	.6
CLASS 9/	.3	6.6	.0	58.8	.5	.7	.0	.9	13.7	.8	.5	.1	4.7	11.8	.5
CLASS 10/	2.6	5.4	.0	6.4	1.0	1.3	4.8	.0	2.9	25.0	5.1	5.8	25.3	6.7	7.7
CLASS 11/	5.8	2.8	.0	33.7	7.7	4.8	3.8	.0	1.0	3.8	13.5	5.8	8.7	7.7	.0
CLASS 12/	9.4	12.5	.0	12.5	.0	.0	15.6	.0	.0	6.2	3.1	21.9	9.4	9.4	.0
CLASS 13/	27.0	3.8	.0	22.1	2.9	1.1	.8	.0	.8	4.1	2.7	2.9	24.1	7.2	.6
CLASS 14/	9.2	6.5	.0	28.1	3.8	1.7	4.6	.0	3.5	4.2	9.8	4.4	14.6	[illegible]	.6
CLASS 15/	39.9	.9	.0	1.1	.1	.1	.6	2.4	.0	1.2	.2	6.7	10.7	[illegible]	36.1

*Spectral Channels 10 and 12 (See Table 5-27)

Table 5-16. Classification Percentages
7 Meter Cell, 4 Best Features*
(4 Spectral Bands)

TRUE CLASS \ CLASSIFICATION		1/	2/	3/	4/	5/	6/	7/	8/	9/	10/	11/	12/	13/	14/	15/
CLASS	1/	38.0	8.0	.8	1.5	.3	.4	.4	.8	.1	7.7	2.7	2.8	14.7	3.4	18.4
CLASS	2/	10.3	9.4	1.1	9.4	1.3	3.4	.7	1.7	1.7	16.1	4.7	1.2	16.8	18.8	3.2
CLASS	3/	7.4	4.1	4.0	31.5	.5	5.9	2.5	4.1	2.8	4.1	4.9	4.1	6.0	17.1	.9
CLASS	4/	2.4	2.6	3.1	35.6	1.2	13.2	.9	3.3	4.7	3.0	8.7	1.2	3.3	16.5	.3
CLASS	5/	.1	.0	.0	15.2	30.7	27.6	6.7	.5	.3	.3	12.4	3.0	.0	2.8	.2
CLASS	6/	.5	.2	1.1	19.3	.9	36.3	1.6	4.6	6.7	4.5	9.6	5.9	.2	8.4	.1
CLASS	7/	5.0	.8	.0	.6	6.9	10.3	26.7	.0	.0	.3	41.1	1.9	4.2	2.2	.0
CLASS	8/	7.0	3.3	.0	1.6	1.6	14.3	.2	14.5	10.4	21.5	1.8	.4	4.5	18.2	1.0
CLASS	9/	.0	.4	1.2	60.1	.3	12.9	.0	5.6	11.4	.5	.4	.3	.0	6.9	.0
CLASS	10/	19.2	6.1	1.0	7.4	.0	9.3	1.9	5.8	2.2	15.1	5.4	5.8	6.4	9.9	4.5
CLASS	11/	3.8	1.9	.0	30.8	4.8	2.9	7.7	1.0	1.0	3.8	17.3	1.9	5.8	13.5	1.9
CLASS	12/	3.1	3.1	.0	12.5	.0	9.4	12.5	.0	3.1	6.2	3.1	31.2	6.2	9.4	.0
CLASS	13/	29.3	3.8	.6	18.9	.8	1.7	.6	.6	2.4	8.5	3.4	1.8	11.1	12.3	4.1
CLASS	14/	9.8	4.4	2.1	21.2	1.3	6.9	1.9	3.5	5.0	6.2	11.3	6.3	2.7	15.6	1.7
CLASS	15/	35.8	1.5	.4	.2	.0	.0	.4	.0	.0	1.5	.3	1.9	2.6	.3	55.2

*Spectral Channels 1, 8, 10, and 12 (See Table 5-27)

Table 5-17. Classification Percentages
7 Meter Cell, 7 Best Features*
(6 Spectral Bands, 1 Textural Feature)

TRUE CLASS \ CLASSIFICATION		1/	2/	3/	4/	5/	6/	7/	8/	9/	10/	11/	12/	13/	14/	15/
CLASS	1/	47.7	7.5	1.0	1.0	.3	.8	.6	.0	.0	7.5	.4	2.6	17.7	2.0	10.2
CLASS	2/	12.9	14.9	6.3	9.5	2.6	2.7	.3	.5	.4	18.0	4.8	1.6	16.5	7.5	1.3
CLASS	3/	8.5	3.3	18.2	25.2	.9	8.4	3.0	1.7	1.6	5.2	7.8	4.0	3.0	8.9	.3
CLASS	4/	3.3	1.6	5.4	35.4	2.4	12.7	1.0	3.3	2.8	3.5	8.0	1.2	2.3	17.0	.2
CLASS	5/	.2	.0	.2	8.2	44.0	25.5	12.9	.1	.7	1.2	5.0	1.1	.0	.9	.0
CLASS	6/	1.4	.0	2.2	20.3	2.0	33.8	1.7	5.3	3.5	6.8	4.7	5.2	.5	12.4	.0
CLASS	7/	5.3	.3	.3	1.1	9.2	6.7	39.2	.0	.0	1.7	30.0	2.8	3.1	.6	.0
CLASS	8/	3.9	3.7	4.5	2.7	2.0	17.6	.8	25.8	2.5	18.7	2.7	.6	3.3	10.5	.6
CLASS	9/	.0	.1	12.1	41.6	.4	12.4	.0	4.1	20.6	2.1	1.3	.1	.1	4.9	.0
CLASS	10/	17.0	3.2	3.5	5.4	1.0	7.4	1.9	3.2	3.8	28.2	4.8	3.8	10.9	3.8	1.9
CLASS	11/	6.7	4.0	6.7	21.2	4.8	2.9	5.8	1.0	1.9	9.6	17.3	4.8	4.8	10.6	1.0
CLASS	12/	3.1	3.1	12.5	3.1	.0	9.4	3.1	.0	.0	3.1	3.1	46.9	.0	12.5	.0
CLASS	13/	29.6	4.0	9.0	17.2	.2	2.7	1.1	.9	.3	5.9	4.7	1.5	18.6	[illegible]	.6
CLASS	14/	[illegible]	2.5	8.1	16.7	3.8	9.2	2.5	3.5	1.3	6.0	8.1	6.0	3.3	27.7	.4
CLASS	15/	59.7	.2	.0	.7	.0	.0	.8	.0	.0	1.8	.6	2.8	4.0	.3	29.3

*Spectral Channels 1, 8, 9, 10, 11, and 12 (See Table 5-27); Textural Feature 51 (See Table 5-12).

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Table 5-18. Classification Percentages
7 Meter Cell, 13 Best Features*
(7 Spectral Bands, 6 Texture Features)

TRUE CLASS \ CLASSIFICATION															
CLASS 1/	47.5	4.4	.1	.1	1.0	.1	2.2	.3	.0	8.9	.6	5.2	13.4	[illegible]	10.8
CLASS 2/	10.2	22.6	4.2	6.2	2.3	.8	.9	.1	1.9	16.8	5.5	5.5	7.9	12.9	2.2
CLASS 3/	[illegible]	4.7	18.7	10.0	1.7	5.4	4.9	1.7	2.5	6.8	12.5	10.9	2.5	10.8	2.4
CLASS 4/	.9	3.0	7.6	14.2	2.4	9.0	.9	3.3	8.2	3.0	11.3	14.8	1.4	16.8	.3
CLASS 5/	.1	.3	.1	.7	53.4	8.0	23.2	1.2	.0	.8	6.4	3.7	.1	2.1	.2
CLASS 6/	.0	1.6	2.9	11.2	4.4	25.6	2.4	7.8	5.6	4.5	5.8	13.9	1.7	12.7	.0
CLASS 7/	3.1	.6	.3	.0	11.7	1.9	46.7	.0	.0	.8	26.9	2.3	3.6	.8	.8
CLASS 8/	1.0	2.0	2.9	.8	5.7	5.1	5.7	31.4	3.7	13.7	7.4	4.1	9.4	6.2	1.0
CLASS 9/	.0	.5	6.1	10.9	1.1	8.0	.0	4.9	59.0	1.9	2.0	3.5	.0	2.1	.0
CLASS 10/	7.1	4.5	2.2	1.6	.3	4.8	5.8	4.8	2.9	30.4	8.3	3.5	10.3	4.5	9.0
CLASS 11/	4.8	.0	6.7	5.8	4.8	1.0	9.6	5.8	1.9	9.6	21.2	6.7	4.3	13.5	3.8
CLASS 12/	.0	.0	.0	.0	.0	6.2	12.5	3.1	.0	.0	15.6	59.4	.0	3.1	.0
CLASS 13/	5.6	4.1	9.0	[illegible]	4.8	1.8	1.7	1.8	.0	6.2	10.5	4.9	30.0	3.4	11.7
CLASS 14/	5.4	3.1	7.5	8.5	6.3	4.2	3.8	4.6	.4	5.8	11.7	11.2	2.1	21.0	4.4
CLASS 15/	19.8	.0	.1	.0	.2	.0	3.0	.0	.0	1.6	1.2	1.5	6.6	.1	66.0

*Spectral Channels 1, 2, 8, 9, 10, 11, and 12 (See Table 5-27); Textural Features 50-55 (See Table 5-12).

Table 5-19. Classification Percentages
14 Meter Cell, 2 Best Features*
(2 Spectral Bands)

TRUE CLASS \ CLASSIFICATION		1/	2/	3/	4/	5/	6/	7/	8/	9/	10/	11/	12/	13/	14/	15/
CLASS	1/	36.2	17.7	.0	.2	.0	1.5	.2	3.9	.9	14.9	.0	7.5	12.1	2.8	2.2
CLASS	2/	12.4	23.4	1.3	15.6	.3	2.7	.0	4.0	.8	9.7	.3	2.4	15.3	11.8	.0
CLASS	3/	7.3	13.0	2.5	32.0	1.9	3.2	4.4	.3	.9	2.5	3.5	1.9	4.1	22.5	.0
CLASS	4/	2.8	14.9	2.1	35.8	4.5	6.6	1.0	.3	3.5	2.1	5.9	.7	4.2	15.6	.0
CLASS	5/	2.3	.0	.8	33.6	17.2	3.1	17.3	.0	3.4	[illegible]	9.7	11.2	.6	.5	.0
CLASS	6/	14.3	7.1	.6	15.8	8.3	6.2	4.9	2.4	4.3	4.3	7.7	8.3	7.3	8.5	.0
CLASS	7/	2.8	2.2	.0	2.8	18.9	6.1	33.9	.0	.0	3.9	24.4	3.9	.6	.6	.0
CLASS	8/	10.2	20.3	.8	1.2	.0	15.6	.0	12.9	.0	7.4	2.7	.8	14.8	12.9	.4
CLASS	9/	.0	10.9	.5	55.6	.0	1.9	.0	.8	16.2	.3	.3	.0	2.7	10.6	.3
CLASS	10/	10.9	13.5	.6	3.8	1.9	2.6	5.1	7.7	2.6	20.5	4.5	3.8	10.9	4.5	7.1
CLASS	11/	5.8	13.5	.0	25.0	15.4	7.7	3.8	.0	.0	5.8	9.6	[illegible]	1.9	5.8	.0
CLASS	12/	12.5	18.7	.0	12.5	.0	.0	12.5	.0	.0	.0	6.2	[illegible]	12.5	6.2	.0
CLASS	13/	32.0	11.0	1.2	18.9	1.8	1.8	.9	.3	.3	11.9	1.2	1.2	9.5	7.8	.3
CLASS	14/	8.5	16.9	.4	22.7	8.5	3.5	4.6	1.9	1.9	4.6	5.8	3.1	5.0	11.2	1.5
CLASS	15/	44.7	.6	.0	.4	.0	.6	1.4	5.5	.0	7.9	.2	3.5	1.4	1.0	32.9

*Spectral Channels 10 and 12 (See Table 5-27)

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Table 5-20. Classification Percentages
14 Meter Cell, 4 Best Features*
(4 Spectral Bands)

TRUE CLASS \ CLASSIFICATION		1/	2/	3/	4/	5/	6/	7/	8/	9/	10/	11/	12/	13/	14/	15/
CLASS	1/	41.6	8.2	.2	.2	.0	.0	.4	1.1	.0	7.1	.0	1.3	20.3	.9	18.7
CLASS	2/	9.4	15.1	1.1	7.0	.0	1.6	.5	1.6	.8	13.4	1.6	5.4	24.2	16.4	1.9
CLASS	3/	5.4	6.0	4.4	23.4	.0	4.4	3.5	3.8	2.5	4.7	3.2	9.8	5.4	22.2	1.3
CLASS	4/	2.8	3.5	3.1	35.4	1.4	12.5	.7	5.6	4.9	3.1	3.1	7.6	5.2	12.2	.0
CLASS	5/	.0	.0	.2	12.7	35.1	35.9	5.5	.5	.5	.6	6.0	2.5	.0	.3	.3
CLASS	6/	.4	.0	.9	19.0	.2	40.0	1.7	9.0	4.3	3.8	6.4	8.8	.0	5.6	.0
CLASS	7/	6.7	.0	.6	.6	2.2	25.6	29.4	.0	.0	.0	27.2	1.1	5.0	1.7	.0
CLASS	8/	5.5	1.2	.0	1.2	.8	20.3	.0	27.7	3.1	23.8	.0	3.1	3.9	9.0	.4
CLASS	9/	.0	.0	.5	51.6	.0	17.0	.0	7.7	15.4	.5	.0	2.9	.0	4.3	.0
CLASS	10/	19.2	2.6	.6	5.1	.0	9.0	1.9	7.7	2.6	18.6	2.6	10.3	6.4	7.1	6.4
CLASS	11/	1.9	3.8	1.9	25.0	1.9	3.8	9.6	3.8	.0	5.8	15.4	3.8	9.6	11.5	1.9
CLASS	12/	6.2	.0	.0	6.2	.0	18.7	25.0	.0	.0	.0	.0	37.5	.0	6.2	.0
CLASS	13/	32.3	2.7	.9	14.6	.0	4.6	.9	.6	.9	6.1	1.8	4.0	15.5	10.4	4.6
CLASS	14/	8.8	4.2	1.5	18.5	1.9	7.7	3.5	3.1	3.8	6.9	7.3	10.4	4.2	10.6	1.5
CLASS	15/	35.6	.0	.0	.4	.0	.0	1.2	.2	.0	.8	.0	.8	3.5	[illegible]	57.3

*Spectral Channels 1, 8, 9, and 12 (See Table 5-27)

Table 5-21. Classification Percentages
14 Meter Cell, 7 Best Features*
(7 Spectral Bands)

TRUE CLASS \ CLASSIFICATION	1/	2/	3/	4/	5/	6/	7/	8/	9/	10/	11/	12/	13/	14/	15/
CLASS 1/	45.0	5.8	.0	.0	.0	.4	.0	.9	.0	6.0	.0	.2	18.5	1.9	21.1
CLASS 2/	15.1	14.5	2.2	5.4	1.1	2.2	.3	3.2	.0	18.0	2.7	.8	14.8	16.9	3.0
CLASS 3/	7.0	5.1	15.8	18.0	.3	5.1	3.8	6.0	1.3	5.7	9.5	4.4	3.2	13.0	1.9
CLASS 4/	2.4	3.8	4.5	36.1	2.4	11.8	.7	4.9	2.8	5.2	7.6	1.4	1.4	14.2	.7
CLASS 5/	.2	.0	.0	3.8	46.8	30.4	8.0	.5	.3	1.4	3.4	2.9	.0	2.3	.2
CLASS 6/	1.1	.0	2.8	17.5	2.4	36.8	1.9	6.0	1.7	9.4	4.3	8.8	1.1	6.4	.0
CLASS 7/	5.6	.6	.6	.6	10.0	8.8	33.3	.0	.0	3.3	30.6	2.8	.6	2.2	1.1
CLASS 8/	4.7	2.0	.8	2.0	1.2	20.7	.8	31.2	1.2	21.9	2.3	2.0	2.3	6.2	.8
CLASS 9/	.0	.0	6.4	40.4	.0	12.0	.0	8.8	23.1	5.3	1.1	.3	.0	2.7	.0
CLASS 10/	16.0	3.2	2.6	1.9	.6	5.1	.6	6.4	3.8	31.4	5.8	7.1	6.4	2.6	6.4
CLASS 11/	5.8	1.9	9.6	17.3	1.9	3.8	5.8	.0	1.2	11.5	17.3	3.8	5.8	11.5	1.9
CLASS 12/	6.2	.0	12.5	12.5	.0	12.5	12.5	.0	.0	12.5	.0	31.2	.0	.0	.0
CLASS 13/	33.2	4.9	7.6	12.8	.0	4.6	.9	.0	.6	6.1	4.0	1.5	15.5	6.7	1.5
CLASS 14/	8.8	4.2	6.2	18.1	4.2	8.8	3.1	4.2	1.9	6.9	9.2	5.8	4.6	13.7	1.2
CLASS 15/	47.2	.2	.0	.2	.0	.2	.0	.2	.0	1.0	.2	2.2	1.4	1.0	46.3

*Spectral Channels 1, 2, 8, 9, 10, 11, and 12 (See Table 5-27)

Table 5-22. Classification Percentages
14 Meter Cell, 7 Best Features*
(6 Spectral Bands, 1 Texture Feature)

TRUE CLASS \ CLASSIFICATION		1/	2/	3/	4/	5/	6/	7/	8/	9/	10/	11/	12/	13/	14/	15/
CLASS	1/	24.8	11.2	.4	.2	.0	.4	.4	.2	.2	3.2	.4	.4	12.9	1.5	43.5
CLASS	2/	9.1	25.5	3.0	8.9	.8	1.9	.3	.3	.0	14.9	2.7	.3	19.6	8.3	4.6
CLASS	3/	[illegible].5	7.0	21.[illegible]	20.6	.3	5.4	4.1	1.6	2.2	4.4	8.9	1.9	4.7	9.5	4.4
CLASS	4/	.7	2.4	4.2	38.2	1.7	11.5	.3	2.1	3.8	3.8	5.6	.3	3.5	19.4	2.1
CLASS	5/	.0	.0	.0	5.2	47.1	30.2	9.0	.2	.3	1.5	4.9	.8	.0	.5	.3
CLASS	6/	.2	.2	1.9	19.9	.4	38.2	1.1	4.9	2.8	7.3	4.9	4.1	1.3	12.2	.6
CLASS	7/	3.9	.6	.0	1.7	11.7	7.2	34.4	.0	.0	2.8	33.3	1.1	1.1	.0	2.2
CLASS	8/	1.2	3.5	1.2	.8	1.6	20.3	.8	28.9	2.3	18.4	2.7	.0	7.4	9.0	2.0
CLASS	9/	.0	.3	9.3	37.5	.3	11.7	.0	2.7	29.0	1.1	1.9	.0	.0	6.4	.0
CLASS	10/	12.2	9.0	2.6	3.8	.0	5.8	.6	4.5	3.8	28.2	8.3	5.1	3.8	1.9	10.3
CLASS	11/	1.9	7.7	5.8	15.4	.0	1.9	3.8	.0	1.9	7.7	26.9	.0	5.8	15.4	5.8
CLASS	12/	.0	.0	12.5	6.2	.0	12.5	.0	6.2	.0	.0	12.5	37.5	6.2	.0	6.2
CLASS	13/	9.1	6.7	7.9	15.[illegible]	.0	3.0	1.2	.0	1.2	3.7	4.6	.6	20.1	3.0	22.9
CLASS	14/	5.0	4.2	6.8	19.6	2.3	8.8	1.2	5.4	1.2	3.1	8.1	5.8	3.8	18.5	6.2
CLASS	15/	9.4	.0	.0	.6	.0	.2	.0	.0	.0	.8	.0	2.0	3.0	.6	83.5

*Spectral Channels 1, 2, 8, 9, 11,and 12 (See Table 5-27); Textural Feature 51 (See Table 5-12)

Table 5-23. Classification Percentages
14 Meter Cell, 10 Best Features*
(7 Spectral Bands, 3 Texture Features)

TRUE CLASS \ CLASSIFICATION															
CLASS 1/	37.5	1.5	.0	.0	.0	.0	.2	.4	.0	6.2	.0	1.0	17.0	2.2	33.4
CLASS 2/	13.2	22.3	1.9	11.8	.5	1.6	.3	.0	1.1	16.4	2.4	.8	12.9	13.2	1.6
CLASS 3/	4.7	5.4	17.7	26.6	.3	6.0	4.1	3.8	.9	4.4	6.0	6.0	1.6	7.9	4.4
CLASS 4/	1.0	4.2	3.8	35.1	1.4	10.4	.3	2.8	6.6	4.2	4.5	5.6	1.4	17.4	1.4
CLASS 5/	.3	.0	.0	5.1	47.1	27.3	8.9	.3	.0	1.5	5.1	3.4	.0	1.1	.0
CLASS 6/	.6	.6	1.5	18.6	1.1	36.8	1.3	4.9	1.3	7.5	3.6	8.1	.6	13.2	.2
CLASS 7/	3.9	.0	.6	1.7	10.6	5.0	36.7	.0	.0	3.9	32.8	1.7	1.7	.0	1.7
CLASS 8/	1.6	1.2	2.3	1.2	1.2	16.0	2.3	29.3	5.9	19.9	3.5	1.6	6.2	4.7	1.2
CLASS 9/	.0	.0	3.7	35.6	.0	11.2	.0	4.5	41.5	2.4	.3	.3	.0	.5	.0
CLASS 10/	7.7	2.6	1.9	5.8	.0	6.4	1.3	3.2	1.3	34.0	7.7	5.1	8.3	2.6	12.2
CLASS 11/	3.8	.0	7.7	17.3	1.9	3.8	.0	5.8	.0	11.5	19.2	5.8	7.7	11.5	3.8
CLASS 12/	6.2	.0	12.5	.0	.0	12.5	12.5	.0	.0	.0	6.2	48.7	.0	6.2	.0
CLASS 13/	21.[illegible]	3.7	7.0	14.6	.0	4.3	.6	1.8	.0	7.3	3.4	2.7	20.1	3.0	10.4
CLASS 14/	5.8	1.9	6.5	19.2	2.7	5.8	1.5	5.4	.4	6.9	6.5	8.5	4.6	18.8	5.4
CLASS 15/	22.6	.0	.0	.2	.0	.2	.0	.0	.0	.6	.0	2.2	1.8	1.0	71.3

*Spectral Channels 1, 2, 8, 9, 10, 11, and 12 (See Table 5-27); Textural Features 50, 51, and 52 (See Table 5-12)

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Table 5-24. Classification Percentages
56 Meter Cells, 2 Features*
(2 Spectral Bands)

TRUE CLASS \ CLASSIFICATION		1/	2/	3/	4/	5/	6/	7/	8/	9/	10/	11/	12/	13/	14/	15/
CLASS	1/	42.4	6.8	.0	.0	6.3	.0	7.9	.5	.0	9.4	.0	.0	3.7	.5	22.5
CLASS	2/	16.2	18.4	.0	5.9	.5	15.1	2.2	17.8	.5	15.1	.0	.5	3.2	3.8	.5
CLASS	3/	3.9	11.8	.0	28.3	3.9	3.1	.0	9.4	.8	12.6	.0	.8	.0	22.8	2.4
CLASS	4/	.0	10.4	.0	27.8	.0	13.2	.7	7.6	6.9	9.7	.0	1.4	.0	20.8	1.4
CLASS	5/	12.6	3.7	.0	.4	35.4	.4	16.3	4.1	.0	21.5	.0	.0	.0	5.7	.0
CLASS	6/	.6	9.9	.0	15.1	.6	22.7	.0	25.0	7.0	6.4	.0	5.8	.0	7.0	.0
CLASS	7/	17.8	7.8	.0	.0	14.4	.0	20.0	.0	.0	34.4	.0	1.1	.0	4.4	.0
CLASS	8/	4.7	28.9	.0	6.2	.0	26.6	1.6	7.8	9.4	10.9	.0	.0	3.9	.0	.0
CLASS	9/	.0	1.1	.0	16.6	.0	41.2	.5	10.7	26.7	.5	.0	1.1	.0	1.6	.0
CLASS	10/	5.1	23.1	.0	10.3	.0	2.6	5.1	15.4	.0	7.7	.0	7.7	.0	12.8	10.3
CLASS	11/	.0	23.1	.0	7.7	.0	.0	7.7	7.7	.0	38.5	.0	7.7	.0	7.7	.0
CLASS	12/	.0	.0	.0	.0	.0	.0	.0	.0	.0	50.0	.0	.0	.0	25.0	.0
CLASS	13/	11.0	29.3	.0	[illegible].8	2.4	6.1	1.2	9.8	2.4	8.5	.0	1.2	13.4	3.7	1.2
CLASS	14/	7.7	18.5	.0	[illegible].8	1.5	9.2	1.5	10.8	.0	16.9	.0	9.2	.0	18.8	.0
CLASS	15/	1[illegible].9	2.8	.0	.0	.8	.0	.0	.0	.0	.0	.0	.0	4.7	.0	79.8

*Spectral Channels 10 and 12 (See Table 5-27)

Table 5-25. Classification Percentages
50 Meter Cells, 4 Features*
(4 Spectral Bands)

TRUE CLASS \ CLASSIFICATION	1/	2/	3/	4/	5/	6/	7/	8/	9/	10/	11/	12/	13/	14/	15/
CLASS 1/	91.1	.0	.0	.0	.0	.0	.0	.0	.0	.5	.0	.0	2.6	.0	5.8
CLASS 2/	9.2	5.8	1.1	.0	9.7	2.7	.0	3.2	1.6	9.7	.0	12.4	35.7	8.6	.0
CLASS 3/	7.9	1.6	11.8	25.2	3.9	1.5	2.4	.8	.8	2.4	3.1	8.7	11.0	17.3	1.6
CLASS 4/	.0	.7	12.5	38.9	6.9	7.6	.7	2.8	4.9	2.8	5.6	6.2	3.5	5.6	1.4
CLASS 5/	.0	.0	.0	.0	68.7	19.9	6.9	.0	.0	.0	1.2	3.3	.0	.0	.0
CLASS 6/	.6	.0	3.5	14.5	5.2	52.3	1.2	5.2	1.7	1.2	8.7	5.2	.6	.0	.0
CLASS 7/	2.2	.0	6.7	.0	1.1	15.6	56.7	.0	.0	.0	8.9	3.3	5.6	.0	.0
CLASS 8/	3.9	.0	.0	.0	.0	16.4	3.1	26.6	9.4	29.7	.0	.0	10.9	.0	.0
CLASS 9/	.0	.0	.5	40.6	3.7	14.4	.0	2.7	37.4	.0	.0	.5	.0	.0	.0
CLASS 10/	15.4	.0	5.1	.0	.0	5.1	.0	15.4	5.1	23.1	5.1	2.6	5.1	12.8	5.1
CLASS 11/	7.7	.0	.0	23.1	7.7	7.7	.0	.0	.0	15.4	15.4	.0	23.1	.0	.0
CLASS 12/	.0	.0	25.0	.0	.0	.0	25.0	.0	.0	.0	.0	50.0	.0	.0	.0
CLASS 13/	36.6	.0	7.3	13.4	4.9	.0	1.2	1.2	1.2	2.4	.0	7.3	15.9	1.2	7.3
CLASS 14/	13.8	.0	9.2	13.8	7.7	.0	4.6	4.6	6.2	4.6	6.2	9.2	7.7	12.3	.0
CLASS 15/	41.1	.0	.0	.0	.4	.4	.0	.0	.0	.0	.0	1.6	.4	.0	56.1

*Spectral Channels 1, 8, 9, and 12 (See Table 5-27)

Table 5-26. Classification Percentages
56 Meter Cells, 7 Features*
(7 Spectral Bands)

TRUE CLASS \ CLASSIFICATION	1/	2/	3/	4/	5/	6/	7/	8/	9/	10/	11/	12/	13/	14/	15/
CLASS 1/	48.7	1.6	.0	.0	.0	.0	.0	.0	.0	.5	.0	.5	3.1	.0	45.5
CLASS 2/	10.8	23.2	1.1	1.1	.5	2.7	.0	4.3	.5	11.9	.0	8.1	8.1	25.4	2.2
CLASS 3/	2.4	10.2	19.[illegible]	15.7	.8	1.6	2.4	.8	.8	3.9	7.1	7.1	.8	19.7	7.1
CLASS 4/	.0	2.1	6.9	47.2	.0	10.4	.7	2.1	3.5	4.2	3.5	4.9	2.8	10.4	1.4
CLASS 5/	.0	.0	.0	.4	63.8	22.8	5.3	.0	.0	1.2	4.1	1.2	.0	1.2	.0
CLASS 6/	.6	.0	1.2	21.5	.0	54.7	2.3	3.5	.0	5.2	4.7	4.1	.0	1.7	.6
CLASS 7/	1.1	.0	3.3	.0	.0	15.6	52.2	.0	.0	4.4	14.4	5.6	2.2	.0	1.1
CLASS 8/	3.1	2.3	.8	.8	.0	26.6	1.6	33.6	7.0	18.0	.0	.0	3.1	.8	2.3
CLASS 9/	.0	.0	2.7	28.9	.5	13.9	.0	2.7	41.2	6.4	1.1	.5	.0	2.1	.0
CLASS 10/	7.7	.0	5.1	.0	.0	2.6	.0	5.1	.0	51.3	5.1	5.1	5.1	.0	12.8
CLASS 11/	15.4	7.7	15.4	.0	.0	.0	15.4	.0	7.7	23.1	7.7	7.7	.0	.0	.0
CLASS 12/	.0	.0	25.0	.0	.0	.0	25.0	.0	.0	.0	.0	50.0	.0	.0	.0
CLASS 13/	11.0	3.7	15.9	8.5	.0	1.2	.0	2.4	1.2	4.9	2.4	7.3	28.0	2.4	11.0
CLASS 14/	6.2	9.2	7.7	13.8	3.1	4.6	3.1	.0	3.1	12.3	3.1	9.2	7.7	16.9	.0
CLASS 15/	11.5	.0	.0	.4	.0	.4	.0	.0	.0	.8	.0	2.0	.4	.4	84.2

*Spectral Channels 1, 2, 8, 9, 10, 11, and 12 (See Table 5-27)

TABLE 5-27. ORDERING OF SPECTRAL AND TEXTURAL FEATURES FOR HONEYWELL BALTIMORE LAND USE DATA

Seven Optimum Features

7 m Data	14 m Data	56 m Data
9.3 - 11.7 μm (12)	9.3 - 11.7 μm (12)	9.3 - 11.7 μm (12)
1.0 - 1.4 μm (10)	0.46 - 0.49 μm (2)	0.46 - 0.49 μm (2)
0.41 - 0.49μm (1)	0.41 - 0.49 μm (1)	0.41 - 0.49 μm (1)
0.62 - 0.70μm (8)	0.62 - 0.70 μm (8)	0.62 - 0.70 μm (8)
0.57 - 0.94μm (9)	0.52 - 0.94 μm (9)	0.57 - 0.94 μm (9)
2.0 - 2.60μm (11)	2.0 - 2.60 μm (11)	2.0 - 2.60 μm (11)
1/56 m texture (51)	1/56 m texture (51)	1.0 - 1.40 μm (10)

NOTE: Features are not necessarily in the order selected by the program. Numbers in parentheses are spectral channel or textural feature number.

TABLE 5-28. PERCENT CORRECT CLASSIFICATION 15 MARYLAND LEVEL III CLASSES

Spectral-Spatial Features \ Resolution	7 m	14 m	56 m
2 Best Spectral	18.0	19.1	21.1
4 Best Spectral	23.5	27.0	37.5
7 Best Spectral		29.2	41.5
6 Spectral 1 Spatial	29.2	33.5	
7 Spectral 3 Spatial		34.1	
7 Spectral 6 Spatial	36.5		

56 m resolution 7 spectral channel accuracy is the highest of all. As far as overall average classification accuracy goes, spectral discrimination dominates and the coarse resolution 56 m simulated sensor data is best. This result is surprising and if this conclusion is generally applicable, it is a contradiction of the popular wisdom. The first objection that the reader might raise is: Is the fundamental 7 m data really 7 m resolution? Figures 5-12 and 5-13 provide the answer. The autocorrelations for the residential areas were computed. Note the zero crossings of 10 m in the x-direction and 12 m in the y-direction. This is consistent with resolutions of 10 and 12 meters in the x, y directions respectively and that the scene probably does contain frequencies at approximately 3 cycles/50 m. But as the channel ordering results show, it is the low frequencies that do the work, not the high. In fact, the results strongly suggest that total pattern size should have been increased to at least 112 meters, thus obtaining even lower frequencies for the spatial features. This would probably have improved the overall classification accuracy from its present low level.

Table 5-29 shows that, while the above discussion is valid for overall performance, there are individual classes where accuracy improves with final resolution. At each resolution the set of spectral/spatial features which gave the best performance was selected. At 7 m resolution, this selection was 7 spectral channels and 6 spatial features. At 14 m, 7 spectral and 3 spatial was selected, and at 56 m, the selection was 7 spectral channels. The justification is clear. Given that the sensor has 7 spectral channels at each resolution, the spatial features are free (the resolution is not). The institutional classifications, colleges, secondary schools, hospitals, military installations, are improved somewhat by improved resolution. Residential and commercial classifications are, for all practical purposes, unchanged by resolution changes.

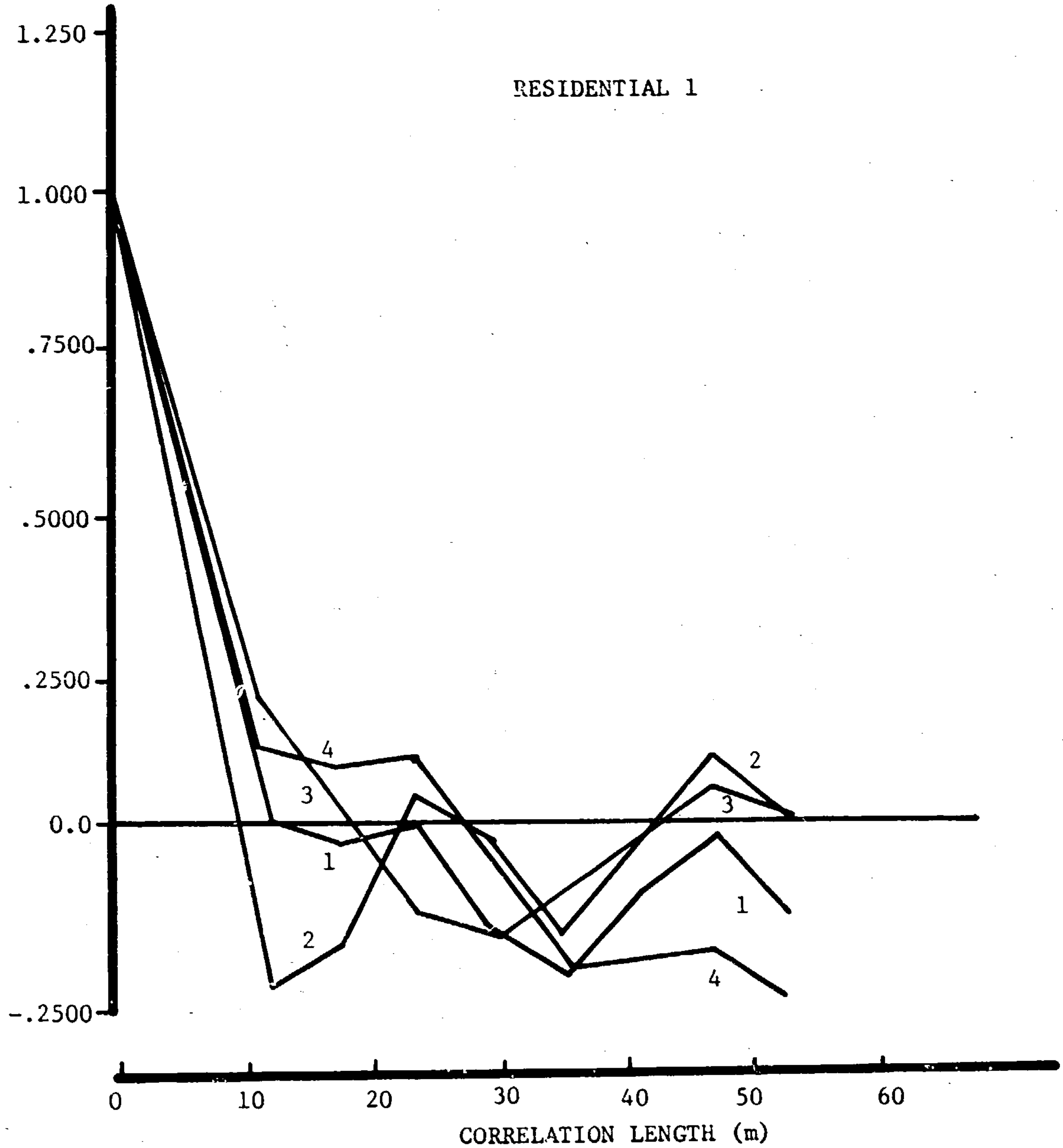

FIGURE 5-12. AUTO-CORRELATION IN X-DIRECTION
RHO (K)

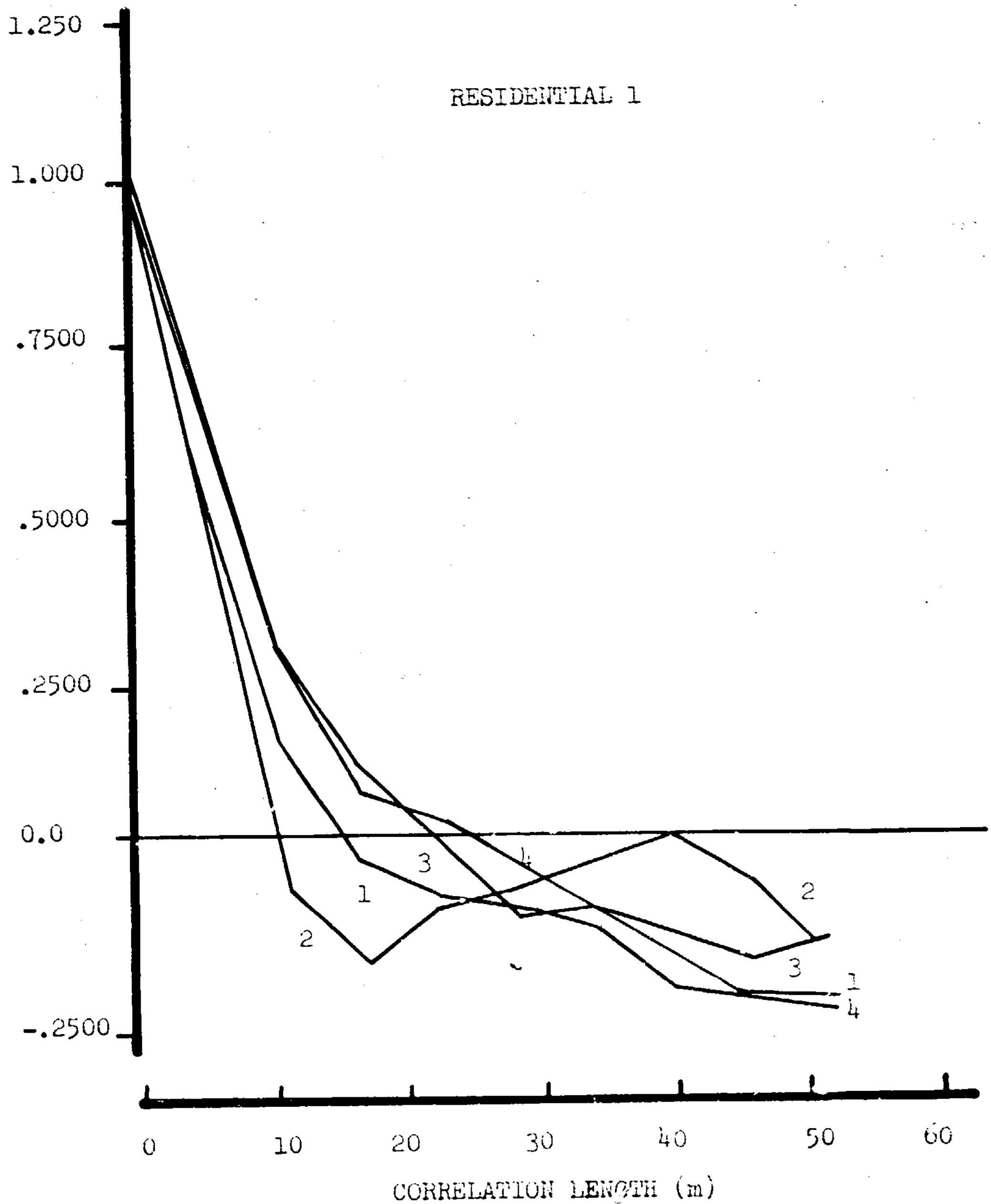

FIGURE 5-13. AUTO-CORRELATION IN Y-DIRECTION RHO (K)

TABLE 5-29. CLASS ACCURACIES

Class \ Resolution	7 m	14 m	56 m
1	47.5	37.5	48.7
2	22.6	22.3	23.2
3	18.7	17.7	19.7
4	14.2	35.1	47.2
5	53.4	47.1	63.8
6	25.6	36.8	54.7
7	46.7	36.7	52.2
8	31.4	29.3	33.6
9	59.0	41.5	41.2
10	30.4	34.0	51.3
11	21.2	19.2	7.7
12	59.4	48.7	50.0
13	30.0	20.1	28.0
14	21.0	18.8	16.9
15	66.0	71.3	84.2

In view of the low classification accuracies obtained for Anderson Level III, classification was next performed for Anderson Level II classes. This classification was accomplished by aggregating the class data from Table 5-15 through 5-26. Two aggregates were made. One aggregation of classes produced the Anderson Level II classes. The second aggregation was oriented towards improving classification accuracy at a coarser use level. Table 5-30 presents this class aggregation.

Table 5-31 through 5-54 present the performance matrices for these two aggregations. Table 5-55 presents a summary of the overall weighted averages for each resolution and feature set. The trends in this Table are the same as before only more pronounced. This result might have been expected since the Level II classes are coarser. The Remote Sensing Classification shows high classification accuracies at the expense of utility of the classification. It should be regarded as a first attempt to find a useful counterpart for the Anderson II classification scheme which produces better remote sensing classification, a useful project beyond the scope of this study.

Figure 5-14 tells the whole story. Improved resolution does not improve urban land use classification accuracy as had originally been assumed at the study's inception. In fact, overall performance decreases with improved resolution. The reason is apparent. Spectral features dominate the overall classification accuracy. One might argue that another method of handling spatial features would have reversed the results. It might improve overall accuracies. Improvements such as addition of lower frequencies in the spatial features and use of spatial features more directed towards "matched" filtering an object size would improve accuracy but not the relation of accuracy to resolution. Every piece of evidence produced herein leads to this conclusion.

TABLE 5-30. URBAN LAND USE CLASS AGGREGATION

AGGREGATION #1

Designation Number	Anderson Level II Class	Honeywell Designation Classes (Table 5-13)
1	11	1, 2
2	12	3, 4
3	13	5, 6
4	15	7, 8, 9, 10
5	16	11, 12, 13, 14
6	19	15

AGGREGATION #2

Designation Number	Remote Sensing Classification (Table 5-13)
1	1, 2, 13, 14, 15
2	3, 12
3	4, 5, 6, 9, 11
4	7
5	8, 10

TABLE 5-31. Classification Percentages - Aggregation #1
7 Meter Cell, 2 Best Features*
(2 Spectral Bands)

TRUE CLASS \ CLASSIFICATION	1, 2	3, 4	5, 6	7, 8, 9, 10	11, 12, 13, 14	15
1, 2	28.4	8.3	1.7	16.0	42.6	3.1
3, 4	11.8	41.8	3.6	7.9	34.8	0.1
5, 6	5.2	19.5	14.9	24.4	36.0	0
7, 8, 9, 10	10.0	26.6	2.3	19.2	40.4	1.6
11, 12, 13, 14	23.0	25.2	5.2	9.0	37.2	0.5
15	40.8	1.1	0.2	4.1	17.7	36.1

Average, Correct Identification 29.6
Weighted Average, Correct Identification 27.1

*Spectral Channels 10 and 12 (See Table 5-27)

TABLE 5-32. Classification Percentages - Aggregation #1
7 Meter Cell, 4 Best Features*
(4 Spectral Bands)

TRUE CLASS \ CLASSIFICATION	1, 2	3, 4	5, 6	7, 8, 9, 10	11, 12, 13, 14	15
1, 2	34.3	5.9	2.5	14.0	31.6	11.7
3, 4	8.5	37.0	10.2	12.7	30.9	0.7
5, 6	0.4	[illegible]	49.5	12.0	20.7	0.2
7, 8, 9, 10	8.1	25.7	14.0	28.2	23.1	1.0
11, 12, 13, 14	22.8	21.7	5.3	14.5	32.8	2.9
15	37.3	0.6	0	1.9	5.0	55.2

Average, Correct Identification 39.5
Weighted Average, Correct Identification 39.1

*Spectral Channels 1, 8, 10, and 12 (See Table 5-27)

Table 5-33. Classification Percentages - Aggregation #1
7 Meter Cell, 7 Best Features*
(6 Spectral Bands, 1 Texture Feature)

TRUE CLASS \ CLASSIFICATION	1, 2	3, 4	5, 6	7, 8, 9, 10	11, 12, 13, 14	15
1, 2	43.1	8.1	2.9	13.1	26.5	6.3
3, 4	8.5	42.1	12.1	11.1	25.9	0.3
5, 6	0.7	14.3	55.5	15.9	13.6	0
7, 8, 9, 10	6.4	24.5	14.4	36.7	17.6	0.5
11, 12, 13, 14	23.0	25.5	7.5	11.0	32.6	0.5
15	60.1	0.7	0	2.4	7.7	29.4

Average, Correct Identification 39.9
Weighted Average, Correct Identification 41.7

*Spectral Channels 1, 8, 9, 10, 11 and 12 (See Table 5-27); Textural Feature 51 (See Table 5-12)

Table 5-34. Classification Percentages - Aggregation #1
7 Meter Cell, 13 Best Features*
(7 Spectral Bands, 6 Texture Features)

TRUE CLASS \ CLASSIFICATION	1, 2	3, 4	5, 6	7, 8, 9, 10	11, 12, 13, 14	15
1, 2	43.4	4.7	2.0	15.1	28.0	6.8
3, 4	6.9	25.4	9.2	15.6	41.6	1.4
5, 6	0.9	6.3	48.2	23.1	21.3	0.1
7, 8, 9, 10	3.6	8.3	9.7	55.9	20.7	1.9
11, 12, 13, 14	8.6	13.5	8.6	13.2	48.1	7.9
15	19.8	0	0.2	4.5	9.4	66.0

Average, Correct Identification 47.8
Weighted Average, Correct Identification 47.9

*Spectral Channels 1, 2, 8, 9, 10, 11, and 12 (See Table 5-27); Textural Features 50-55 (See Table 5-12)

Table 5-35. Classification Percentages - Aggregation #1
14 Meter Cell, 2 Best Features*
(2 Spectral Bands)

TRUE CLASS \ CLASSIFICATION	1, 2	3, 4	5, 6	7, 8, 9, 10	11, 12, 13, 14	15
1, 2	45.8	7.7	2.2	17.6	25.7	1.2
3, 4	19.0	36.1	8.0	7.6	29.3	0
5, 6	10.3	26.9	17.9	18.9	26.1	0
7, 8, 9, 10	17.3	23.6	10.2	24.9	22.8	1.3
11, 12, 13, 14	33.8	21.5	8.4	13.0	22.4	0.8
15	45.3	0.4	0.6	14.8	6.1	32.9

Average, Correct Identification 30.0
Weighted Average, Correct Identification 28.9

*Spectral Channels 10 and 12 (See Table 5-27)

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Table 5- Classification Percentages - Aggregation #1
14 Meter Cell, 4 Best Features*
(4 Spectral Bands)

TRUE CLASS \ CLASSIFICATION	1, 2	3, 4	5, 6	7, 8, 9, 10	11, 12, 13, 14	15
1, 2	38.5	3.8	0.7	12.1	33.6	11.2
3, 4	8.9	32.9	8.9	13.9	34.6	0.7
5, 6	0.2	15.8	58.1	12.0	13.8	0.2
7, 8, 9, 10	6.5	21.7	18.8	34.0	17.8	1.1
11, 12, 13, 14	23.3	18.0	7.0	13.3	35.4	3.1
15	35.4	0.4	0	2.2	4.5	57.3

Average, Correct Identification 42.7
Weighted Average, Correct Identification 43.1

*Spectral Channels 1, 8, 9, and 12 (See Table 5-27)

Table 5-37. Classification Percentages - Aggregation #1
14 Meter Cell, 7 Best Features*
(7 Spectral Bands)

TRUE CLASS \ CLASSIFICATION	1, 2	3, 4	5, 6	7, 8, 9, 10	11, 12, 13, 14	15
1, 2	41.4	3.3	1.7	13.4	27.2	13.0
3, 4	9.3	37.1	9.6	15.2	27.5	1.3
5, 6	0.5	10.7	61.3	13.8	13.6	0
7, 8, 9, 10	6.0	19.8	14.9	42.7	15.2	1.4
11, 12, 13, 14	25.0	22.6	8.2	12.3	30.5	1.4
15	47.4	0.2	0.2	1.2	4.7	46.3

Average, Correct Identification 43.2
Weighted Average, Correct Identification 44.9

*Spectral Channels 1, 2, 8, 9, 10, 11, and 12 (See Table 5-27)

Table 5-38. Classification Percentages - Aggregation #1
14 Meter Cell, 7 Best Features*
(6 Spectral Bands, 1 Textural Feature)

TRUE CLASS \ CLASSIFICATION	1, 2	3, 4	5, 6	7, 8, 9, 10	11, 12, 13, 14	15
1, 2	35.4	5.6	1.4	9.0	22.2	26.2
3, 4	6.9	42.2	9.3	11.3	26.8	3.5
5, 6	0.2	12.1	61.2	13.1	12.9	0.4
7, 8, 9, 10	5.6	20.0	14.9	38.7	18.0	2.6
11, 12, 13, 14	12.3	24.5	6.4	8.5	33.7	14.5
15	9.4	0.6	0.2	0.8	5.5	83.5

Average, Correct Identification 49.1
Weighted Average, Correct Identification 48.1
*Spectral Channels 1, 2, 8, 9, 11 and 12 (See Table 5-27); Textural Feature 51 (See Table 5-12)

Table 5-39. Classification Percentages - Aggregation #1
14 Meter Cell, 10 Best Features*
(7 Spectral Bands, 3 Textural Features)

TRUE CLASS \ CLASSIFICATION	1, 2	3, 4	5, 6	7, 8, 9, 10	11, 12, 13, 14	15
1, 2	37.4	6.1	1.0	11.7	24.3	19.3
3, 4	7.8	41.7	8.9	13.6	25.0	3.0
5, 6	0.7	11.3	59.1	12.5	16.3	0
7, 8, 9, 10	3.1	17.9	13.3	47.9	15.2	2.6
11, 12, 13, 14	15.9	23.3	6.3	12.2	34.9	7.6
15	22.8	0.2	0.2	0.6	4.9	71.3

Average, Correct Identification 48.7
Weighted Average, Correct Identification 48.6

*Spectral Channels 1, 2, 8, 9, 10, 11, and 12 (See Table 5-27); Tectural Features 50, 51, and 52 (See Table 5-12)

Table 5-40. Classification Percentages - Aggregation #1
56 Meter Cell, 2 Best Features*
(2 Spectral Bands)

TRUE CLASS \ CLASSIFICATION	1, 2	3, 4	5, 6	7, 8, 9, 10	11, 12, 13, 14	15
1, 2	42.0	2.9	10.9	26.6	5.9	11.7
3, 4	12.9	28.0	10.3	24.0	22.9	1.8
5, 6	13.9	6.5	30.6	40.4	8.6	0
7, 8, 9, 10	17.8	9.7	28.2	38.3	5.2	0.9
11, 12, 13, 14	32.3	10.4	8.5	28.0	20.1	0.6
15	14.6	0	0.8	0	4.7	79.8

Average, Correct Identification 39.8
Weighted Average, Correct Identification 39.8

*Spectral Channels 10 and 12 (See Table 5-27)

Table 5-41. Classification Percentages - Aggregation #1
56 Meter Cell, 4 Best Features*
(4 Spectral Bands)

TRUE CLASS \ CLASSIFICATION	1, 2	3, 4	5, 6	7, 8, 9, 10	11, 12, 13, 14	15
1, 2	53.7	0.5	6.1	7.2	29.3	2.9
3, 4	4.8	44.6	10.3	8.9	29.9	1.5
5, 6	0.2	7.4	75.8	7.9	8.6	0
7, 8, 9, 10	2.9	19.1	16.2	52.0	9.2	0.5
11, 12, 13, 14	24.4	22.0	6.7	12.8	30.5	3.7
15	41.1	0	0.8	0	2.0	56.0

Average, Correct Identification 52.1
Weighted Average, Correct Identification 55.2

*Spectral Channels 1, 8, 9, and 12 (See Table 5-27)

Table 5-42. Classification Percentages - Aggregation #1
56 Meter Cell, 7 Best Features*
(7 Spectral Bands)

TRUE CLASS \ CLASSIFICATION	1, 2	3, 4	5, 6	7, 8, 9, 10	11, 12, 13, 14	15
1, 2	42.3	1.1	1.6	8.5	22.3	24.2
3, 4	7.0	45.4	6.6	9.2	27.7	4.1
5, 6	0.2	9.6	73.4	8.4	8.2	0.2
7, 8, 9, 10	2.5	14.9	17.1	55.0	8.6	2.0
11, 12, 13, 14	15.2	22.6	3.7	15.9	37.2	5.5
15	11.5	0.4	0.4	0.8	2.8	84.2

Average, Correct Identification 56.3
Weighted Average, Correct Identification 57.5

*Spectral Channels 1, 2, 8, 9, 10, 11 and 12 (See Table 5-27)

Table 5-43. Classification Percentages- Aggregation #2
7 Meter Cell, 2 Best Features*
(2 Spectral Bands)

TRUE CLASS \ CLASSIFICATION	1, 2, 13, 14, 15	3, 12	4, 5, 6, 9, 11	7	8, 10
1, 2, 13, 14, 15	67.7	5.7	17.8	1.0	7.9
3, 12	38.1	6.0	47.0	3.9	5.0
4, 5, 6, 9, 11	20.0	8.1	61.3	5.6	5.0
7	10.3	7.8	53.1	27.8	1.4
8, 10	62.7	3.0	17.2	1.9	15.0

Average, Correct Identification 35.6
Weighted Average, Correct Identification 54.7

*Spectral Channels 10 and 12 (See Table 5-27)

Table 5-44. Classification Percentages - Aggregation #2
7 Meter Cell, 4 Best Features *
(4 Spectral Bands)

TRUE CLASS \ CLASSIFICATION	1, 2 13, 14, 15	3, 12	4, 5 6, 9, 11	7	8, 10
1, 2, 13, 14, 15	71.1	3.4	16.1	0.7	8.7
3, 12	35.0	9.3	44.6	3.0	8.1
4, 5, 6, 9, 11	9.8	3.9	78.2	3.1	5.1
7	12.2	1.9	58.9	26.7	0.3
8, 10	38.6	2.8	27.6	0.9	30.2

Average, Correct Identification 43.1
Weighted Average, Correct Identification 64.2

*Spectral Channels 1, 8, 10, and 12 (See Table 5-27)

Table 5-45. Classification Percentages - Aggregation #2
7 Meter Cell, 7 Best Features *
(6 Spectral Bands, 1 Textural Feature)

TRUE CLASS \ CLASSIFICATION	1, 2, 13, 14, 15	3, 12	4, 5, 6, 9, 11	7	8, 10
1, 2, 13, 14, 15	69.8	6.8	14.4	0.9	8.2
3, 12	23.8	24.0	42.5	3.0	6.8
4, 5, 6, 9, 11	9.7	6.2	72.6	5.3	6.2
7	9.2	3.1	46.9	39.2	1.7
8, 10	27.7	6.0	25.6	1.2	39.6

Average, Correct Identification 49.0
Weighted Average, Correct Identification 63.8

*Spectral Channels 1, 8, 9, 10, 11, and 12 (See Table 5-27); Textural Feature 51 (See Table 5-12)

Table 5-46. Classification Percentages - Aggregation #2
7 Meter Cell, 13 Best Features*
(7 Spectral Bands, 6 Textural Features)

TRUE CLASS \ CLASSIFICATION	1, 2, 13, 14, 15	3, 12	4, 5, 6, 9, 11	7	8, 10
1, 2, 13, 14, 15	68.8	8.4	11.9	2.3	8.7
3, 12	24.1	30.9	31.5	5.3	8.3
4, 5, 6, 9, 11	10.3	11.5	62.3	9.3	6.6
7	8.9	2.5	40.8	46.9	0.8
8, 10	25.5	6.6	20.9	5.7	41.4

Average, Correct Identification 50.1
Weighted Average, Correct Identification 60.3

*Spectral Channels 1, 2, 8, 9, 10, 11 and 12 (See Table 5-27); Textural Features 50 - 55 (See Table 5-12)

Table 5-47. Classification Percentages - Aggregation #2
14 Meter Cell, 2 Best Features*
(2 Spectral Bands)

TRUE CLASS \ CLASSIFICATION	1, 2 13, 14, 15	3, 12	4, 5 6, 9, 11	7	8, 10
1, 2, 13, 14, 15	66.3	4.4	14.5	1.2	13.6
3, 12	47.0	5.1	40.4	4.8	2.7
4, 5, 6, 9, 11	22.3	7.2	60.1	7.7	2.6
7	6.1	3.9	52.2	33.9	3.9
8, 10	54.1	2.7	18.0	1.9	23.3

Average, Correct Identification 37.7
Weighted Average, Correct Identification 54.5

*Spectral Channels 10 and 12 (See Table 5-27)

Table 5-48. Classification Percentages - Aggregation #2
14 Meter Cell, 4 Best Features*
(4 Spectral Bands)

TRUE CLASS \ CLASSIFICATION	1, 2, 13, 14, 15	3, 12	4, 5, 6, 9, 11	7	8, 10
1, 2, 13, 14, 15	75.7	4.2	11.4	1.1	7.6
3, 12	38.9	15.4	33.1	4.6	8.2
4, 5, 6, 9, 11	7.1	5.9	77.3	2.8	6.7
7	13.3	1.7	55.5	29.4	0
8, 10	28.1	6.0	22.8	0.7	42.0

Average, Correct Identification 48.0
Weighted Average, Correct Identification 67.3

*Spectral Channels 1, 8, 9 and 12 (See Table 5-27)

Table 5-49. Classification Percentages - Aggregation #2
14 Meter Cell, 7 Best Features*
(7 Spectral Bands)

TRUE CLASS \ CLASSIFICATION	1, 2, 13, 14, 15	3, 12	4, 5, 6, 9, 11	7	8, 10
1, 2, 13, 14, 15	74.6	4.4	11.9	0.6	8.6
3, 12	28.9	21.4	33.7	4.2	11.8
4, 5, 6, 9, 11	8.0	6.6	72.4	3.6	9.4
7	10.0	3.3	50.0	33.3	3.3
8, 10	23.1	5.3	23.5	0.7	47.3

Average, Correct Identification 49.8
Weighted Average, Correct Identification 66.0

*Spectral Channels 1, 2, 8, 9, 10, 11 and 12 (See Table 5-27)

Table 5-50. Classification Percentages - Aggregation #2
14 Meter Cell, 7 Best Features*
(6 Spectral Bands, 1 Textural Feature)

TRUE CLASS \ CLASSIFICATION	1, 2, 13, 14, 15	3, 12	4, 5, 6, 9, 11	7	8, 10
1, 2, 13, 14, 15	76.5	4.8	12.8	0.5	5.7
3, 12	28.3	24.7	37.1	3.9	6.0
4, 5, 6, 9, 11	10.8	4.6	75.3	3.7	5.6
7	7.8	1.1	53.9	34.4	2.8
8, 10	28.4	3.6	25.5	0.7	41.8

Average, Correct Identification 50.5
Weighted Average, Correct Identification 67.7

*Spectral Channels 1, 2, 8, 9, 11 and 12 (See Table 5-27); Textural Feature 51 (See Table 5-12)

Table 5-51. Classification Percentages - Aggregation #2
14 Meter Cell, 13 Best Features*
(7 Spectral Bands, 6 Textural Features)

TRUE CLASS \ CLASSIFICATION	1, 2 13, 14, 15	3, 12	4, 5 6, 9, 11	7	8, 10
1, 2, 13, 14, 15	74.5	5.0	11.9	0.4	8.1
3, 12	23.4	25.5	38.7	4.5	7.8
4, 5, 6, 9, 11	9.3	6.3	74.1	3.5	6.8
7	7.2	2.2	50.0	36.7	3.9
8, 10	21.8	5.1	26.5	1.9	44.7

Average, Correct Identification 51.1
Weighted Average, Correct Identification 66.8

*Spectral Channels 1, 2, 8, 9, 10, 11 and 12 (See Table 5-27); Textural Features 50 - 55 (See Table 5-12)

Table 5-52. Classification Percentages - Aggregation #2
56 Meter Cell, 2 Best Features*
(2 Spectral Bands)

TRUE CLASS \ CLASSIFICATION	1, 2, 13, 14, 15	3, 12	4, 5, 6, 9, 11	7	8, 10
1, 2, 13, 14, 15	70.6	1.0	11.1	2.7	14.6
3, 12	40.5	0.8	35.9	0	22.9
4, 5, 6, 9, 11	18.4	2.0	51.8	5.6	22.2
7	30.0	1.1	14.4	20.0	34.4
8, 10	40.7	1.8	35.3	2.4	19.8

Average, Correct Identification 32.6
Weighted Average, Correct Identification 51.6

*Spectral Channels 10 and 12 (See Table 5-27)

Table 5-53. Classification Percentages - Aggregation #2
56 Meter Cell, 4 Best Features*
(4 Spectral Bands)

TRUE CLASS \ CLASSIFICATION	1, 2, 13, 14, 15	3, 12	4, 5, 6, 9, 11	7	8, 10
1, 2, 13, 14, 15	79.8	6.8	8.5	0.5	4.4
3, 12	38.1	22.1	33.6	3.1	3.1
4, 5, 6, 9, 11	2.9	6.7	84.3	2.6	3.4
7	7.8	10.0	25.6	56.7	0
8, 10	20.4	1.8	23.4	2.4	52.1

Average, Correct Identification 59.0
Weighted Average, Correct Identification 74.2

*Spectral Channels 1, 8, 9, and 12 (See Table 5-27)

Table 5-54. Classification Percentages - Aggregation #2
56 Meter Cell, 7 Best Features*
(7 Spectral Bands)

TRUE CLASS \ CLASSIFICATION	1, 2, 13, 14, 15	3, 12	4, 5, 6, 9, 11	7	8, 10
1, 2, 13, 14, 15	81.7	6.8	5.1	0.3	6.0
3, 12	38.9	28.2	25.2	3.0	4.6
4, 5, 6, 9, 11	5.1	5.0	81.1	2.6	6.2
7	4.4	8.9	30.0	52.2	4.4
8, 10	15.0	3.0	28.1	1.2	52.7

Average, Correct Identification 59.2
Weighted Average, Correct Identification 73.9

*Spectral Channels 1, 2, 8, 9, 10, 11 and 12 (See Table 5-27)

TABLE 5-55. PERCENT CORRECT CLASSIFICATION
TWO CLASSIFICATION AGGREGATES

AGGREGATION #1

Feature Set \ Resolution	ANDERSON LEVEL II 7 m	14 m	56 m
2 Spectral	27.1	28.9	39.8
4 Spectral	39.1	43.1	55.2
7 Spectral		44.9	57.5
7 Best (1 Texture)	41.7		
7 Spectral 3 Spatial		48.6	
7 Spectral 6 Spatial	47.9		

AGGREGATION #2

	REMOTE SENSING CLASSIFICATION		
2 Spectral	54.7	54.5	51.6
4 Spectral	64.2	67.3	74.2
7 Spectral		66.0	73.9
7 Best (1 Texture)	63.8		
7 Spectral 3 Spatial		66.8	
7 Spectral 6 Spatial	60.3		

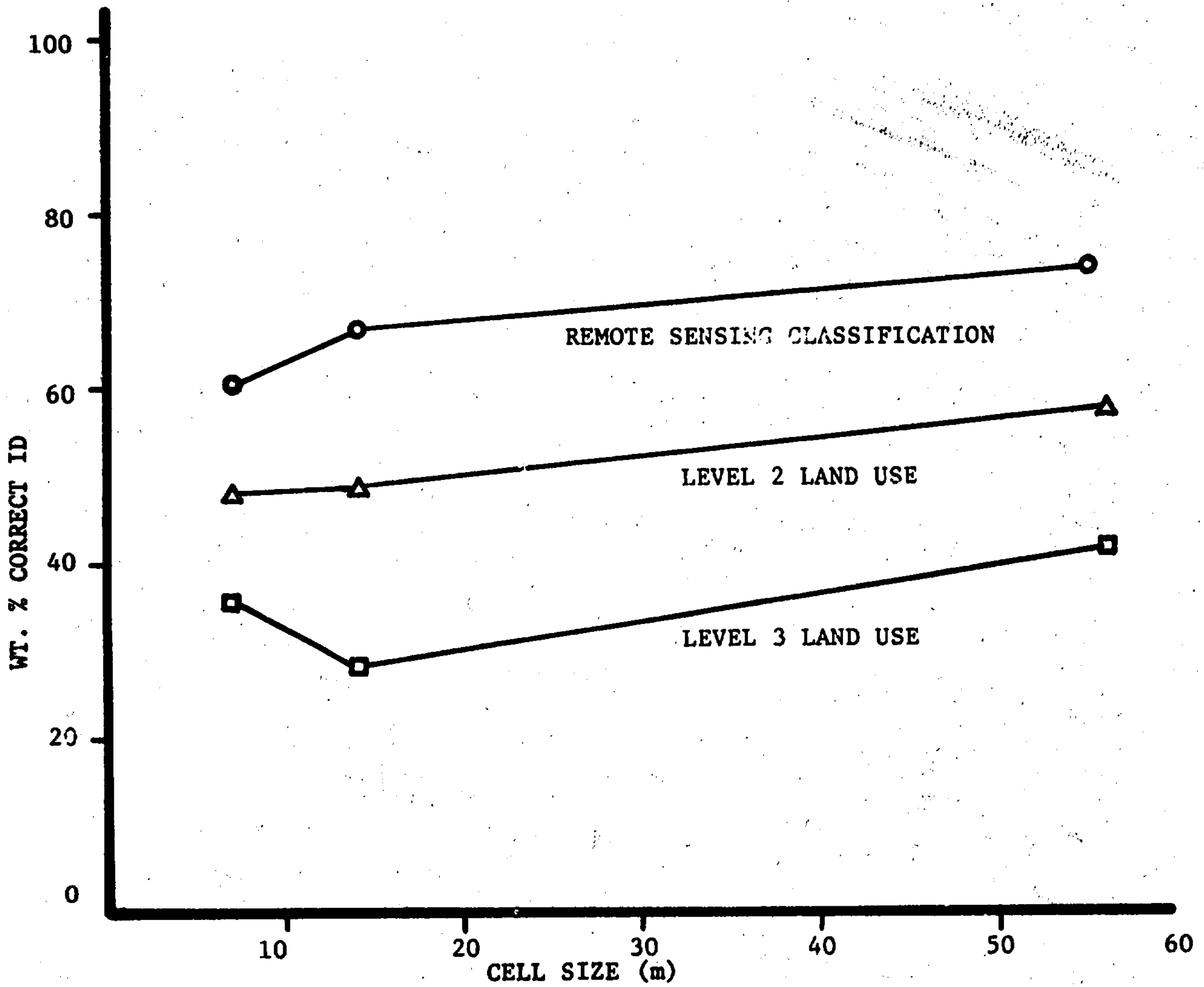

FIGURE 5-14. EFFECTS OF RESOLUTION ON CLASSIFICATION ACCURACY

The reader should be aware that only automatic classification has been considered. Photointerpretative classification, where the dominant features in the classification are spatial, might produce a different result. However, the results of this study are marked enough to question even the assumption concerning photointerpretative results. The powerful technical tool of hindsight leads to the question: What can be seen at 10 m that could not be seen at 60 m?

5.4 CONCLUSIONS AND RECOMMENDATIONS - SPATIAL STUDY

The classification techniques being considered are automatic techniques which can and do handle the spectral information better than a photointerpreter. However, one must grant that a photointerpreter, who does rely on spatial features for classification, handles spatial features far better than any automatic method of spatial feature classification. Spatial resolution, a decisive factor in sensor cost, can be expected to affect spatial measurement and spatial feature classification, both chores the historical task of the photointerpreter. Our study method relied heavily on spectral features and implemented automatically the measurement and spatial feature classification. If a user relies solely on remote sensing photointerpretation, these conclusions may be contrary to the best interests of the photointerpretative craft.

Figure 5-8 certainly shows little change in acreage estimation accuracy by going from 15-30 meters resolution. The smaller fields, 10-20 acres, which do predominate in U. S. agriculture showed a marked decrease in acreage estimate accuracies going from 30-60 meters. This change can be at least partially compensated for by processing techniques (convex mixture, etc.). Thus, if costs were not a factor, 30 m resolution might be indicated but not at the expense of other system specifications.

Figure 5-14 tells the tale for the use of spatial features in urban land use classification. Spatial features are dominated by the spectral features and spectral feature classification improves with degraded resolution. Study results indicate that little is gained by resolutions finer than 60 m. Because of the surprising nature of these results, further study is recommended prior to specification of required spatial resolution.

6
CONCLUSIONS AND RECOMMENDATIONS

6.1 GENERAL

The recommended system presented in this section is based on limited actual data, and thus the weight of the evidence cannot be totally compelling. The evidence is offered as being at least equal to any existing evidence on which to guide decisions and the material presented merits thoughtful consideration. The conclusions and recommendations presented in the following paragraphs are based upon the study results presented in Sections 3 through 5.

6.2 SPECTRAL STUDY CONCLUSIONS

The spectral study addressed the selection of the optimum number, location and width of spectral bands for each of five application disciplines. This selection was based primarily upon a theoretical analysis of applicable literature and upon results of automatic data processing of simulated satellite multispectral scanner data collected over selected discipline test sites. Published theoretical and laboratory band locations and widths were compiled for the Agriculture/Range/Forestry, Geology/Mineral Resources, Hydrology/Water Resources, Urban Land Use, and Marine/Oceanographic user disciplines. Analysis of this published data and the empirical multispectral scanner data results indicated a wide variation in spectral bands required for different applications. The spectral band requirements for each of the disciplines addressed is presented in Table 3-32.

To demonstrate the effect of the number of bands upon classification accuracy, optimum bands from simulated satellite MSS data for the Agriculture, Geology, and Land Use test sites were selected by established processing algorithms. Classification was then conducted using the best 12, 7, and 4 spectral bands from these prioritized lists

of bands for Agriculture and Land Use, and the best 15, 7, and 5 bands for Geology. The effect of this variation in the number of spectral bands upon classification accuracy is shown in Figure 6-1. For the Agriculture and Urban Land Use disciplines, the results show that the classification accuracy remains at approximately the same when 4, 7, or 12 channels are used for classification. This does not necessarily indicate, however, that a four channel system will produce the indicated classification accuracies for both disciplines, since the four bands used to achieve the Agriculture results differed from those used for Urban Land Use classification. The dependence of classification accuracy upon the number of spectral bands for the Geology discipline follows from the relatively large (twenty-one) number of scene materials which were classified. The classification of numerous materials is, however, a representative task of Geology discipline users interested in arid regions such as the White Sands, New Mexico Test Site used in this study. For such geologic applications, the study results indicate that, unlike the Agriculture and Urban Land Use disciplines, a marked increase in classification accuracy will be realized as the number of spectral bands is increased from five to fifteen bands.

Study results indicate that the number of discrete spectral bands required to satisfy the needs of users in all disciplines is prohibitively large. If the requirement is limited to scene classification, as was the case for the empirical position of the study, then classification results of the Agricultural and Urban Land Use discipline support a need for no more than four spectral bands for each discipline.

The seven bands presented in Section 6.5 represent the compromise bands to satisfy the widest range of user needs. The bands were chosen from bands that all disciplines desired, while emphasis was given to Agriculture and Urban Land Use. While spectral study results revealed that perhaps four bands were sufficient for automatic data processing

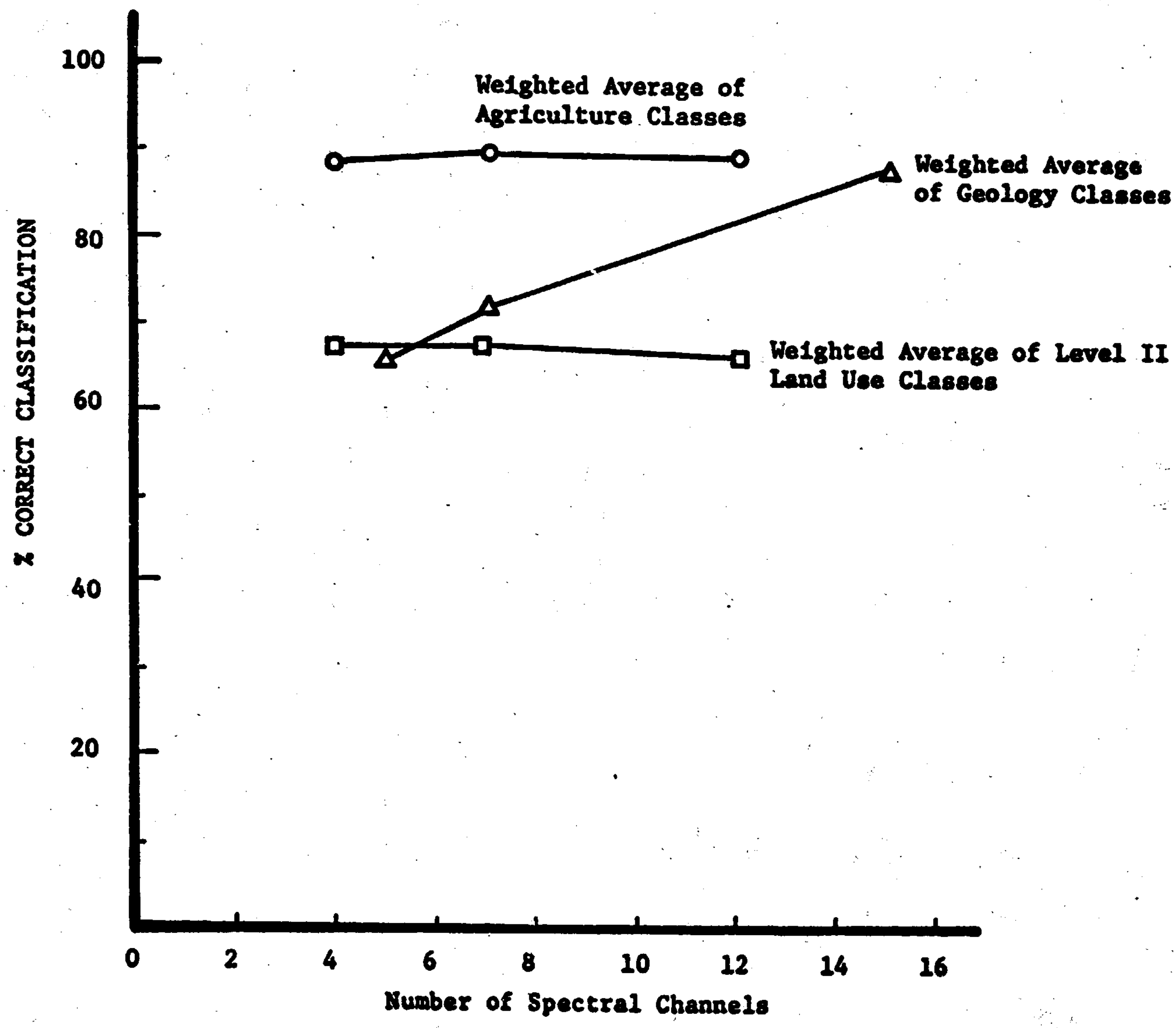

FIGURE 6-1. CLASSIFICATION ACCURACY vs NUMBER OF SPECTRAL BANDS

classification for any one discipline, the four bands required were not the same for each discipline; hence a seven band system seems justified.

6.3 RADIOMETRIC STUDY CONCLUSIONS

This section of the study addressed various user discipline needs for calibration, stability, and signal sensitivity in multispectral scanner designs. These sources of error in the recorded signal levels of a scanner can cause such sizable problems to occur in the automatic classification of features within a scene that little information is obtained. The effects of these sources of signal inaccuracy upon classification accuracy must be taken into account in sensor design in order to produce acceptable information for the users. It is the classification accuracy required by these various users which defines the acceptable error or instability in sensor parameters.

Variations in recording precision, gain, and offset of scanner data were examined in an empirical manner to determine the signal accuracy required of an assumed optimum seven-spectral band orbital scanner for the Agriculture and Land Use disciplines. In addition, theoretical calculations were carried out for water quality and water depth mapping applications to estimate the noise equivalent reflectance difference required in various spectral bands to achieve the information extraction performance required.

Empirical results of the radiometric study are shown in Figures 6-2 through 6-4. Figure 6-2 presents the results of varying the effective NE$\Delta\rho$(NEΔT) for Agriculture and Urban Land Use. As indicated in the figure no appreciable reduction is seen in the accuracy of Agricultural classification until the number of data bits is reduced from 9 to 5. Level II Land Use classification, on the other hand, is affected appreciably when data significance is reduced to only 7 bits. As shown in Figures 6-3 and 6-4, studies of the effect of gain and

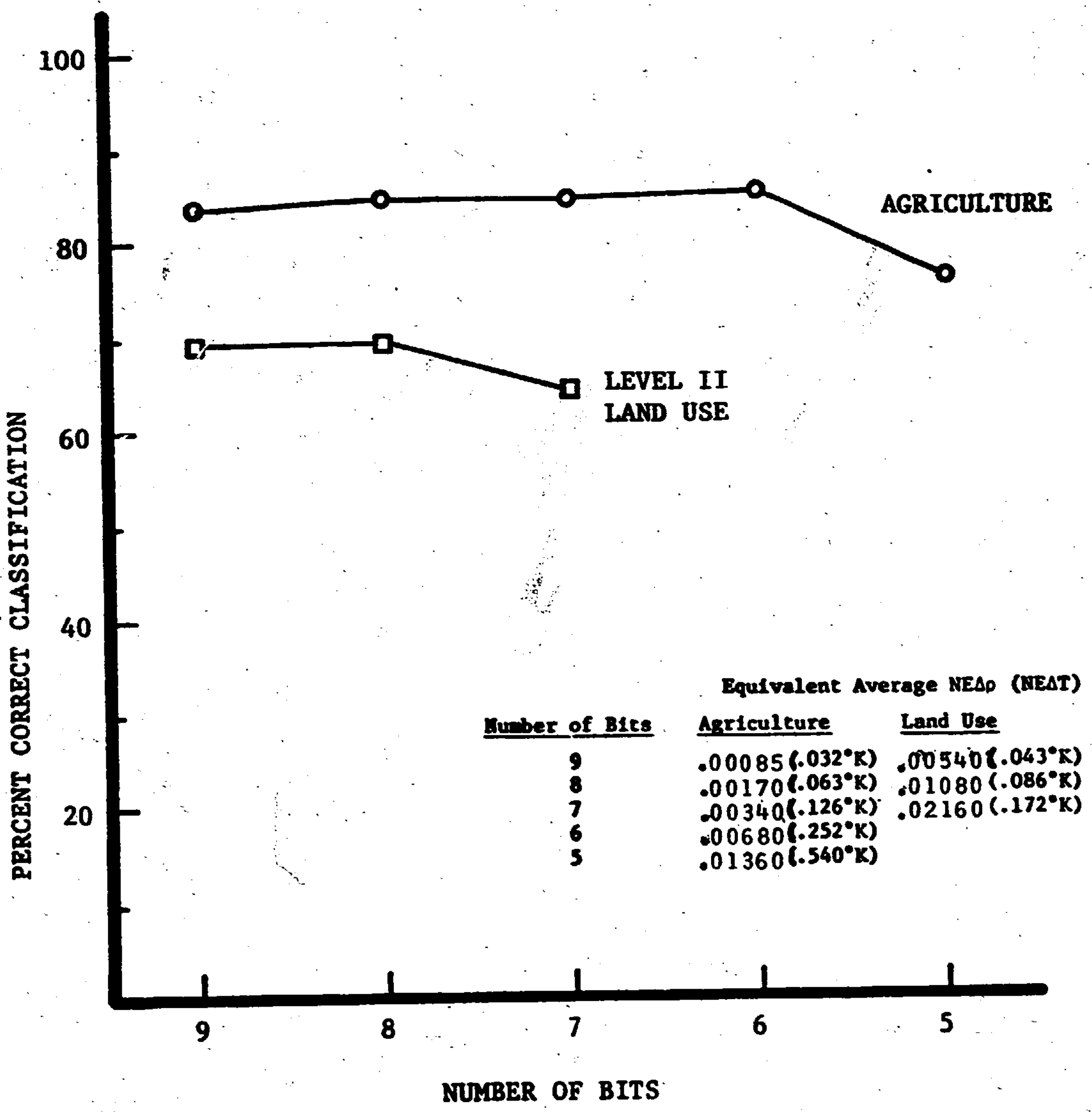

FIGURE 6-2. EFFECTS OF NEΔρ (NEΔT) ON CLASSIFICATION ACCURACY

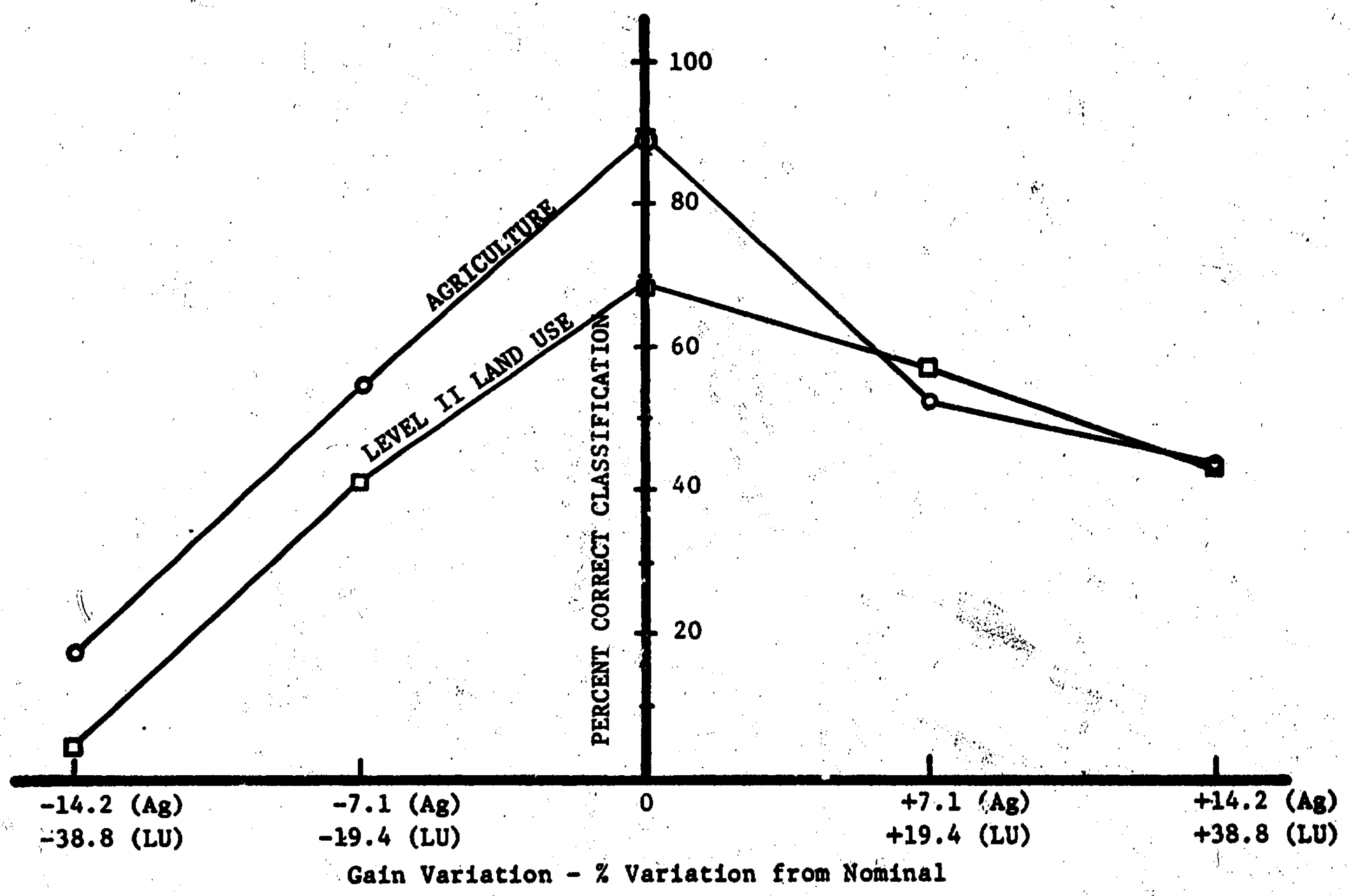

FIGURE 6-3. EFFECTS OF GAIN VARIATION ON CLASSIFICATION ACCURACY

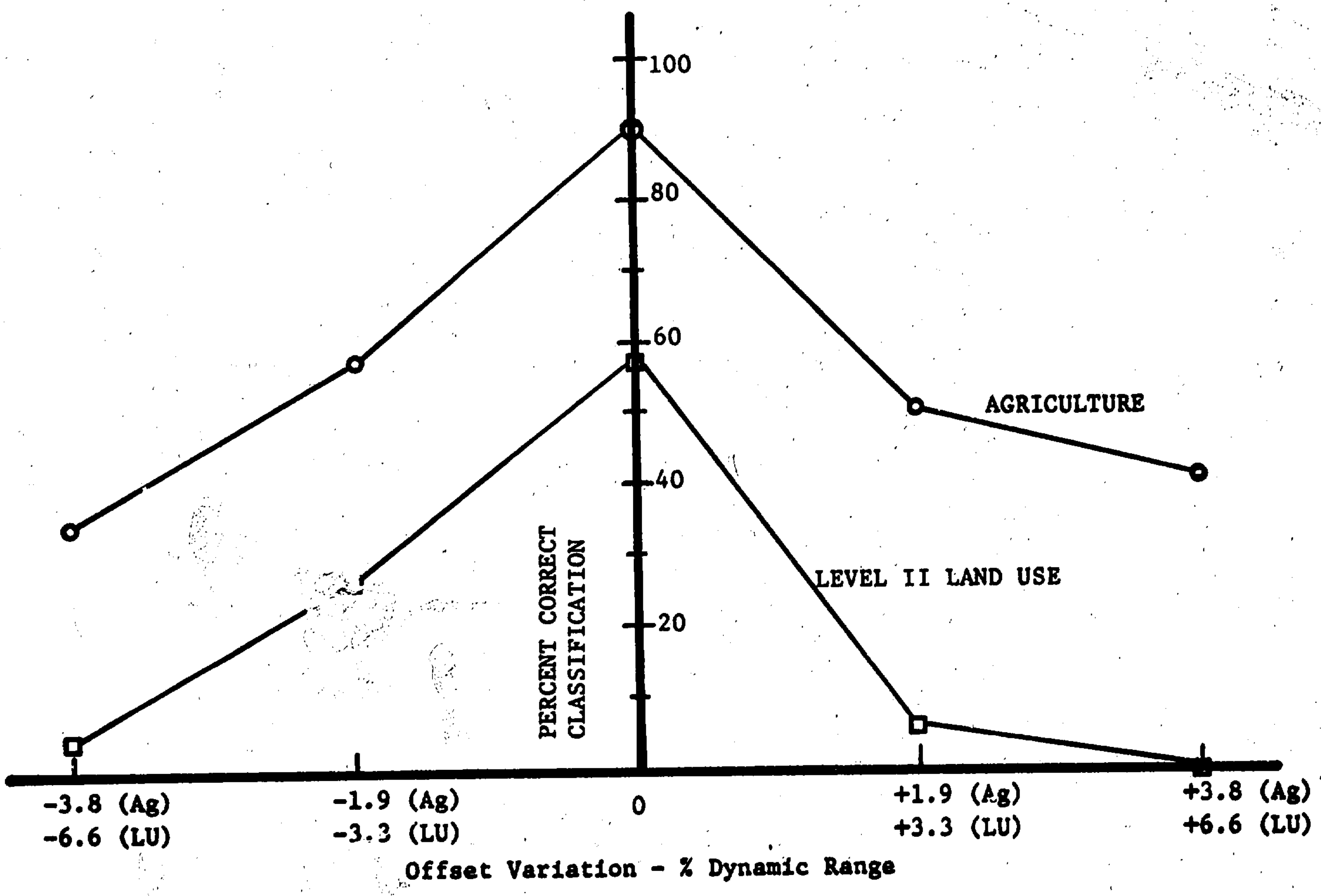

FIGURE 6-4. EFFECTS OF OFFSET VARIATIONS ON CLASSIFICATION ACCURACY

offset variations revealed that gain variations of 1.4 percent and offset variations of 0.38 percent of full scale degrade seven channel Agriculture classification accuracy from about 90 to 85 percent. Gain variations of 8 percent and offset variations of 1 percent of full scale reduced Level II Land Use classification accuracies from 64 to 59 percent.

These results suggest a sensor system with an NE$\Delta\rho$(ΔT) of 0.5 percent (0.5°K) which is stable to within about 1.4 percent of full scale in gain and 0.38 percent of full scale in offset, if Agricultural and Urban Land Use classification accuracies are to be compromised by no more than 5 percent.

The empirical study of radiometric precision requirements indicates that Agriculture and Anderson Level II Land Use classification have less stringent radiometric requirements than Water and Marine Resources. Analysis of radiance levels to be encountered in the recommended bands indicate the need for 8 bit data resolution to achieve the desired NEΔL over the range of radiance (L) encountered. Such data resolution is deemed practical in view of EOS baseline specifications. Because of the large range in expected radiances encountered in some bands, a highly accurate, calibrated AGC system will probably be required.

6.4 SPATIAL STUDY CONCLUSIONS

The spatial study addressed two distinct problem areas; 1) the system spatial resolution, and 2) the utility of combining spatial and spectral features for classification. The system spatial resolution investigation consisted of both a theoretical and an empirical study with the prime source of data for the empirical study being gathered by ERIM's M-7 multispectral scanner. Two separate data sets, one gathered over a Michigan Agricultural area and the other gathered over a Baltimore Urban area, were used in the spatial resolution study.

The Baltimore data set was also used for examining the utility of combining spatial and spectral features for classification.

As might be expected, the theoretical investigation of spatial resolution effects showed that more accurate agriculture field acreage estimates could be obtained as the resolution element decreased in size. Of course, the same improvement resulted when the resolution element size was kept fixed with increasing the field size, thus pointing out that the important factor is the resolution element size relative to the size (and shape) of the field. The study did show that, with certain assumptions, the errors in field acreage estimates could be significant even for ERTS-size resolution elements (80 m) and common field sizes (20-40 acres).

For the empirical study of spatial resolution effects, the effective spatial resolution of the aircraft multispectral scanner data was degraded to simulate the resolution of various satellite MSS systems. As indicated in Figure 6-5, the expected result that Urban Land Use classification and agricultural field acreage accuracy would increase with smaller resolution element size was not totally supported by the empirical results. Although the field acreage estimation accuracy did have a general decrease as resolution element size increased, the trend for larger field sizes was much less marked than was expected. The apparent reason for this trend for larger fields is that the boundary elements (those resolution elements overlapping field boundaries), instead of being primarily unclassified were randomly classified as the available classes. As a result of compensating errors, then, the field acreage accuracy was not highly correlated with resolution size. Urban Land Use classification results, on the other hand, actually improved somewhat with increasing resolution element size.

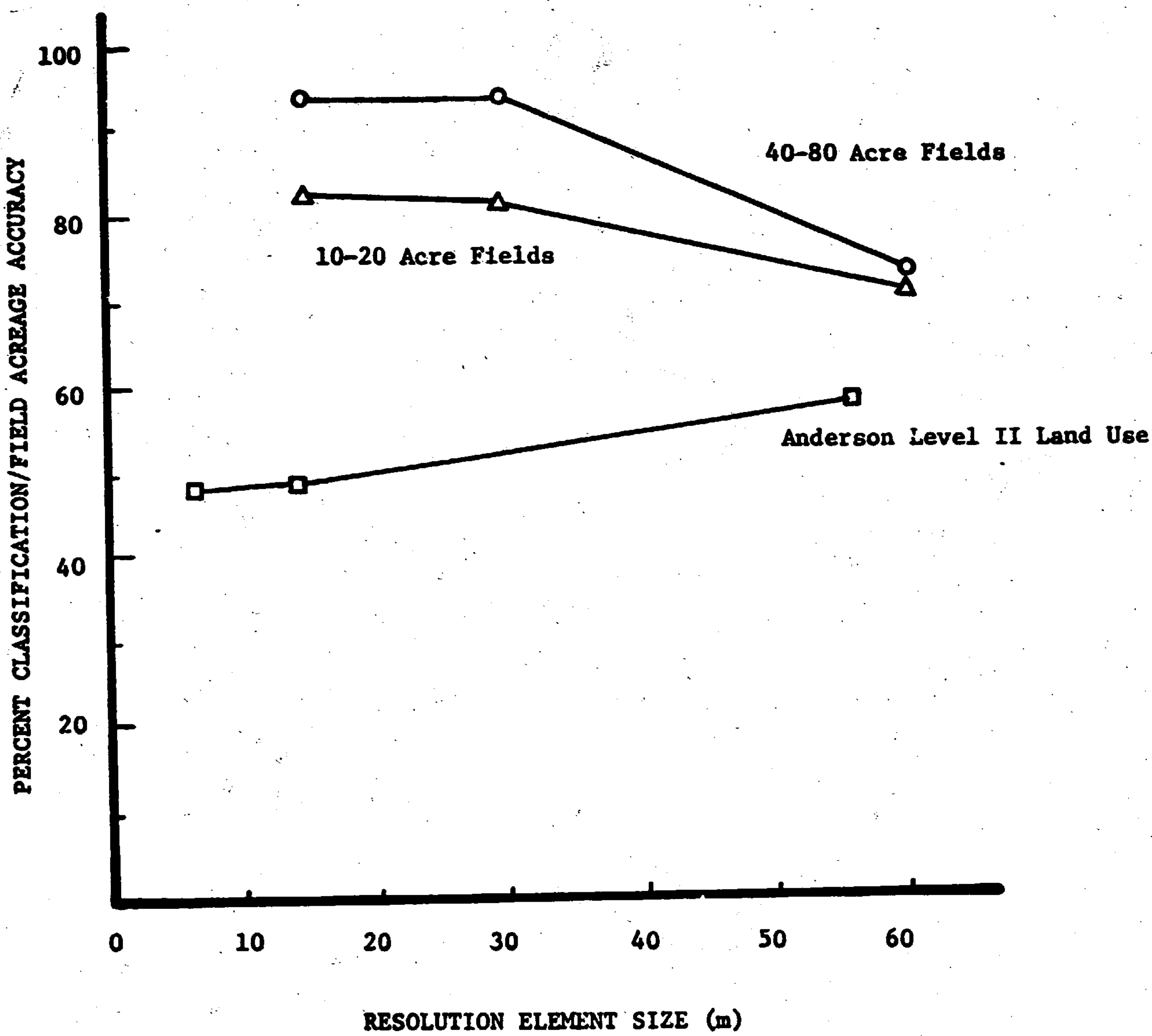

FIGURE 6-5. CLASSIFICATION/ACREAGE ACCURACY vs SPATIAL RESOLUTION

Results of the Baltimore Land Use data processing, where spatial features were used in addition to spectral features, revealed that the most useful spatial information was at a frequency attainable with a 30 m resolution element size, but that the best spatial feature was seventh in order of utility, being preceded by six spectral features. The improvement in classification by adding the best spatial feature in place of the seventh best spectral feature was 4 percent for fifteen State-of-Maryland-defined Level III classes.

The results of this spatial study do not unconditionally support the EOS baseline recommendation of a 30 m resolution element system. In fairness, it should be pointed out that only machine implemented spectral pattern recognition, augmented with some spatial data, were studied. The conclusions reached are not necessarily pertinent to photointerpretation data reduction approaches.

The empirical spatial study results presented herein did not unilaterally support a case for a instantaneous field of view finer than 30 meters, especially when achieving this spatial resolution with the bands we chose would result in high technological risk. For this reason, resolution element size of 30 to 60 meters is tentatively suggested, pending a more thorough study of resolution between 30 and 60 meters.

6.5 RECOMMENDED SYSTEM

Based upon the above conclusions, the following spectral, radiometric and spatial specifications are recommended for a seven band EOS Thematic Mapper optimized to collect data for the Agriculture, Land Use, and Water Resources disciplines:

<u>Spectral Bands</u>

- 0.45-0.52 μm
- 0.52-0.60 μm
- 0.63-0.69 μm
- 0.80-0.95 μm

Spectral Bands (continued)

- 1.55-1.75 μm
- 10.4-12.5 μm
- 0.42-0.48 μm or 8.3-9.3 μm

Radiometric Requirements

- NEΔρ for reflective bands - 0.5% *
- NEΔT for thermal bands - 0.5°K
- Maximum allowable gain variation - 1.4% of full scale
- Maximum allowable offset variation - 0.38% of full scale
- Automatic Gain Control to provide the recommended NEΔρ and NEΔT for reflectances ranging from 2.0% to 60.0% and temperatures raning from 260°K to 340°K

Spatial Resolution

- Recommended IFOV - 30 m to 60 m

*The recommended NEΔρ is based upon the data presented in Tables 4-8 through 4-11. Empirical results do not support this recommendation for the reflective IR portion, due to the uncertainties in the IR data bands.

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APPENDIX A

PERFORMANCE MATRICES FOR RADIOMETRIC STUDY RESULTS

TABLE A-1 PERFORMANCE RESULTS
MICHIGAN AGRICULTURE TEST SITE

30 Meter Data
7 Optimum Channels
9-Bit Data

SCENE CLASS (No. of Pixels)	PER CENT CORRECT CLASSIFICATION	PER CENT MISCLASSIFICATION				
		CORN	SOY-BEANS	RIPE OATS	WOODS	OTHER
CORN (812)	94.1				0.7	5.2
SOYBEANS (284)	73.9	5.3				20.8
RIPE OATS (20)	100.0					
WOODS (860)	96.7	1.9				1.4
OTHER (1168)	84.8	9.5	0.4	1.0	4.2	

Average = 89.9

Wt. Average = 89.6

TABLE A-2 PERFORMANCE RESULTS
MICHIGAN AGRICULTURE TEST SITE

30 Meter
7 Optimum Channels
8-Bit Significance

		PER CENT MISCLASSIFICATION				
SCENE CLASS (No. of Pixels)	PER CENT CORRECT CLASSIFICATION	CORN	SOY-BEANS	RIPE OATS	WOODS	OTHER
CORN (812)	94.1				0.7	5.2
SOYBEANS (284)	70.4	7.8				21.8
RIPE OATS (20)	100.0					
WOODS (860)	96.4	1.9				1.7
OTHER (1168)	85.7	9.8	0.4	0.9	3.1	

Average = 89.3
Wt. Average = 89.5

TABLE A-3 PERFORMANCE RESULTS
MICHIGAN AGRICULTURE TEST SITE

30 Meter Data
7 Optimum Channels
7-Bit Data Significance

SCENE CLASS (No. of Pixels)	PER CENT CORRECT CLASSIFICATION	PER CENT MISCLASSIFICATION				
		CORN	SOY-BEANS	RIPE OATS	WOODS	OTHER
CORN (812)	96.8				0.4	2.8
SOYBEANS (284)	52.1	19.7				28.2
RIPE OATS (20)	95.0					5.0
WOODS (860)	95.0	2.2				2.8
OTHER (1168)	84.7	11.1	0.3	1.0	2.8	

Average = 84.7

Wt. Average = 88.3

TABLE A-4 PERFORMANCE RESULTS
MICHIGAN AGRICULTURE TEST SITE

30 Meter Data
7 Optimum Channels
6-Bit Data Significance

SCENE CLASS (No. of Pixels)	PER CENT CORRECT CLASSIFICATION	PER CENT MISCLASSIFICATION				
		CORN	SOY-BEANS	RIPE OATS	WOODS	OTHER
CORN (812)	98.0					2.0
SOYBEANS (284)	58.5	15.5				26.0
RIPE OATS (20)	95.0					5.0
WOODS (860)	96.1	1.6				2.3
OTHER (1168)	84.2	9.9	0.2			

Average = 84.7

Wt. Average = 88.3

TABLE A-5 PERFORMANCE RESULTS
MICHIGAN AGRICULTURE TEST SITE

30 Meter Data
7 Optimum Channels
5-Bit Data Significance

SCENE CLASS (No. of Pixels)	PER CENT CORRECT CLASSIFICATION	PER CENT MISCLASSIFICATION				
		CORN	SOY-BEANS	RIPE OATS	WOODS	OTHER
CORN (812)	97.9				0.5	1.6
SOYBEANS (284)	52.1	18.7		0.4		28.8
RIPE OATS (20)	70.0					30.0
WOODS (860)	89.2	4.4				6.4
OTHER (1168)	77.1	14.2	1.3	1.9	5.3	

Average = 77.3

Wt. Average = 83.9

TABLE A-6 PERFORMANCE RESULTS
MICHIGAN AGRICULTURE TEST SITE

30 Meter Data
7 Optimum Channels
+1/3 Gain Variation

SCENE CLASS (No. of Pixels)	PER CENT CORRECT CLASSIFICATION	PER CENT MISCLASSIFICATION: CORN	SOY-BEANS	RIPE OATS	WOODS	OTHER
CORN (812)	16.8			.4	61.2	21.6
SOYBEANS (284)	2.8	1.1			7.0	89.1
RIPE OATS (20)	100.0					
WOODS (860)	99.4	.2				.4
OTHER (1168)	63.7	.5		7.8	28.2	

Average = 56.5
Wt. Average = 52.0

TABLE A-7 PERFORMANCE RESULTS
MICHIGAN AGRICULTURE TEST SITE

30 Meter Data
7 Optimum Channels
-1/3 Gain Variation

		PER CENT MISCLASSIFICATION				
SCENE CLASS (No. of Pixels)	PER CENT CORRECT CLASSIFICATION	CORN	SOY-BEANS	RIPE OATS	WOODS	OTHER
CORN (812)	79.0		9.2			11.8
SOYBEANS (284)	29.2					70.8
RIPE OATS (20)	0	5.0				95.0
WOODS (860)	44.8	13.7	26.2			15.3
OTHER (1168)	62.6	5.3	31.9		.2	

Average = 43.1
Wt. Average = 58.5

TABLE A-8 PERFORMANCE RESULTS
MICHIGAN AGRICULTURE TEST SITE

30 Meter Data
7 Optimum Channels
+2/3 Gain Variation

SCENE CLASS (No. of Pixels)	PER CENT CORRECT CLASSIFICATION	PER CENT MISCLASSIFICATION CORN	SOY-BEANS	RIPE OATS	WOODS	OTHER
CORN (812)	0.1			.4	95.7	3.8
SOYBEANS (284)	0			7.8	26.1	66.1
RIPE OATS (20)	50.0					50.0
WOODS (860)	99.6					.4
OTHER (1168)	48.9			12.7	38.4	

Average = 41.9
Wt. Average = 46.8

TABLE A-9 PERFORMANCE RESULTS
MICHIGAN AGRICULTURE TEST SITE

30 Meter Data
7 Optimum Channels
-2/3 Gain Variation

SCENE CLASS (No. of Pixels)	PER CENT CORRECT CLASSIFICATION	PER CENT MISCLASSIFICATION				
		CORN	SOY-BEANS	RIPE OATS	WOODS	OTHER
CORN (812)	0					100.0
SOYBEANS (284)	0					100.0
RIPE OATS (20)	0	10.0				90.0
WOODS (860)	1.0	2.5	1.6			94.9
OTHER (1168)	98.1		1.9			

Average = 19.8
Wt. Average = 37.9

TABLE A-10 PERFORMANCE RESULTS
MICHIGAN AGRICULTURE TEST SITE

30 Meter Data
7 Optimum Channels
+1/3 Offset Variation

		PER CENT MISCLASSIFICATION				
SCENE CLASS (No. of Pixels)	PER CENT CORRECT CLASSIFICATION	CORN	SOY-BEANS	RIPE OATS	WOODS	OTHER
CORN (812)	5.8			.3	80.4	13.5
SOYBEANS (284)	1.8	9.5			9.5	79.2
RIPE OATS (20)	100.0					
WOODS (860)	99.5	.1				.4
OTHER (1168)	58.8	.8		6.9	33.4	

Average = 53.2
Wt. Average = 51.4

TABLE A-11 PERFORMANCE RESULTS
MICHIGAN AGRICULTURE TEST SITE

30 Meter Data
7 Optimum Channels
-1/3 Offset Variation

		PER CENT MISCLASSIFICATION				
SCENE CLASS (No. of Pixels)	**PER CENT CORRECT CLASSIFICATION**	**CORN**	**SOY-BEANS**	**RIPE OATS**	**WOODS**	**OTHER**
CORN (812)	76.4		6.9			16.7
SOYBEANS (284)	38.7					61.3
RIPE OATS (20	10.0					90.0
WOODS (860)	45.8	26.8	17.4			10.0
OTHER (1168)	59.8		38.9		1.3	

Average = 46.1
Wt. Average = 57.9

TABLE A-12 PERFORMANCE RESULTS
MICHIGAN AGRICULTURE TEST SITE

30 Meter Data
7 Optimum Channels
+2/3 Offset Variation

SCENE CLASS (No. of Pixels)	PER CENT CORRECT CLASSIFICATION	PER CENT MISCLASSIFICATION CORN	SOY-BEANS	RIPE OATS	WOODS	OTHER
CORN (812)	0			.3	99.7	
SOYBEANS (284)	0			1.8	50.7	47.5
RIPE OATS (20)	0					100.0
WOODS (860)	58.0					42.0
OTHER (1168)	67.4		.1	4.4	28.1	

Average = 25.1
Wt. Average = 41.2

TABLE A-13 PERFORMANCE RESULTS
MICHIGAN AGRICULTURE TEST SITE

30 Meter Data
7 Optimum Channels
-2/3 Gain Variation

SCENE CLASS (No. of Pixels)	PER CENT CORRECT CLASSIFICATION	PER CENT MISCLASSIFICATION				
		CORN	SOY-BEANS	RIPE OATS	WOODS	OTHER
CORN (812)	0		1.4			98.6
SOYBEANS (284)	0					100.0
RIPE OATS (20)	0	5.0				95.0
WOODS (860)	5.0	0.4	2.4			92.2
OTHER (1168)	95.5	0.3	4.2			

Average = 20.1
Wt. Average = 36.8

TABLE A-14. PERFORMANCE MATRICES - BALTIMORE LAND USE AVERAGE ACCURACY (WEIGHTED) FOR SENSITIVITY VARIATIONS (30 Meter Data, 7 Optimum Channels)

7 Bits	% CORRECT	% ERRORS	
		Commission	Omission
LEVEL I	83.6	10.8	5.6
LEVEL II	63.9	30.5	5.6
LEVEL III	46.1	48.3	5.6

8 Bits	% CORRECT	% ERRORS	
		Commission	Omission
LEVEL I	83.2	10.0	7.8
LEVEL II	64.7	27.5	7.8
LEVEL III	47.4	44.8	7.8

9 Bits	% CORRECT	% ERRORS	
		Commission	Omission
LEVEL I	85.2	8.1	6.7
LEVEL II	67.9	25.4	6.7
LEVEL III	54.9	38.4	6.7

TABLE A-15 **PERFORMANCE MATRICES**
BALTIMORE LAND USE

LEVEL I LAND USE* 7 Channels, 9 Bits, 30 Meters

GROUND TRUTH	AGGREGATED COMPUTER SPECTRAL CLASSES				
	URBAN	AG	FOREST	WATER	UNCLAS.
URBAN (1)	83.9	6.3	1.2		2.0
AGRICULTURE (2)	14.3	71.4	7.2		7.2
FOREST (4)	5.9		94.1		
WATER (5)				12.5	87.5

LEVEL II LAND USE* 7 Channels, 9 Bits, 30 Meters

GROUND TRUTH	AGGREGATED COMPUTER SPECTRAL CLASSES						
	RES	COM/IND	AG	PAST	FOR	WATER	UNCLAS.
RESIDENTIAL (11)	66.3	21.7	6.4	0.6	1.9		3.2
COMMERCIAL/ INDUSTRIAL (12/13)	25.5	52.0	4.1	1.0			17.4
CROPLAND (21)	6.7	6.7	60.0	6.7	6.7		13.3
PASTURE (22)	11.1	3.7	14.8	59.3	7.3		3.7
FOREST Deciduous (41)	5.9				94.1		
WATER (50)						100	

*ANDERSON LAND USE CLASSES ARE SHOWN IN PARENTHESES

TABLE A-16. PERFORMANCE MATRIX, BALTIMORE, MARYLAND

LEVEL III COMPUTER SPECTRAL CLASSIFICATION OF LAND USE 7 Channels, 9 Bits, 30 Meters

GROUND TRUTH	FAM Single Family Res. (111)	APT1 APT2 Multiple Family (112)	RLR SOIL ASPH Commercial (121/122)	MDR DR Industrial (130)	SOIL CROP Cropland (210)	PASTURE Pasture (220)	FOREST Deciduous Forest (410)	Water (500)	Unclassified
Single Family Residential (111)	62.7	16.0		2.7	9.3	1.3	4.0		4.0
Multi-family (112) and Institutional (160)	13.4	41.5	13.4	25.6	3.6				2.4
Commercial (121/122)	11.8	15.7	29.4	31.4	2.0	2.0			7.9
Industrial (13)	6.4	17.0	19.2	23.4	6.4				27.7
Cropland (210)	6.7	6.7			60.0	6.7	6.7		13.3
Pasture (220)	5.9	3.0			11.8	47.1	5.9		3.0
Deciduous Forest (410)	3.0	3.0					94.1		
Water (500)								12.5	87.5

State of Maryland Land Use Classes shown in parentheses.

TABLE A-17 **PERFORMANCE MATRICES**
BALTIMORE LAND USE

LEVEL I LAND USE* 7 Channels, 8 Bits, 30 Meters

GROUND TRUTH	AGGREGATED COMPUTER SPECTRAL CLASSES				
	URBAN	AG	FOREST	WATER	UNCLAS.
URBAN (1)	87.9				
AGRICULTURE (2)	16.7	76.2	7.2		
FOREST (4)	3.0	3.0	74.1		
WATER (5)	5.0		2.5	42.5	50.0

Avg. Correct Class = 75.2 W Water
= 86.1 W/O Water

LEVEL II LAND USE* 7 Channels, 8 Bits, 30 Meters

GROUND TRUTH	AGGREGATED COMPUTER SPECTRAL CLASSES						
	RES	COM/ IND	AG	PAST	FOR	WATER	UNCLAS.
RESIDENTIAL (11)	66.5	20.9	6.3	.6	2.5		3.2
COMMERCIAL/ INDUSTRIAL (12/13)	27.8	60.8	4.1	3.1			4.1
CROPLAND (21)	20.0		60.0	13.3	6.7		
PASTURE (22)	14.7		11.1	66.7	7.4		
FOREST Deciduous (41)	3.0			3.0	74.1		
WATER (50)		5.0			2.5	42.5	50.0

*ANDERSON LAND USE CLASSES ARE SHOWN IN PARENTHESES

Avg. Correct Class = 65.1 W Water
= 69.6 W/O Water

ORIGINAL PAGE IS OF POOR QUALITY

TABLE A-18. PERFORMANCE MATRIX, BALTIMORE, MARYLAND

LEVEL III COMPUTER SPECTRAL CLASSIFICATION OF LAND USE 7 Channels, 8 Bits, 30 Meters

GROUND TRUTH	FAM Single Family Res. (111)	APT1 APT2 Multiple Family (112)	RLR SOIL ASPH Commercial (121/122)	MDR DR Industrial (130)	SOIL CROP Cropland (210)	PASTURE Pasture (220)	FOREST Deciduous Forest (410)	Water (500)	Unclassified
Single Family Residential (111)	54.7	21.3	2.6	1.3	9.3	1.3	5.3		4.0
Multi-family (112) and Institutional (160)	14.5	43.5	12.0	24.1	3.6				2.4
Commercial (121/122)	8.0	20.0	34.0	30.0	2.0	4.0			2.0
Industrial (13)	4.3	23.4	44.7	12.8	6.4	2.1			6.4
Cropland (210)	6.7	13.3			60.0	13.3	6.7		
Pasture (220)	7.4	7.4			11.1	66.7	7.4		
Deciduous Forest (410)	3.0					3.0	94.1		
Water (500)				5.0			2.5	42.5	50.0

State of Maryland Land Use Classes shown in parentheses.

TABLE A-19 PERFORMANCE MATRICES
BALTIMORE LAND USE

LEVEL I LAND USE* 7 Channels, 7 Bits, 30 Meters

GROUND TRUTH	AGGREGATED COMPUTER SPECTRAL CLASSES				
	URBAN	AG	FOREST	WATER	UNCLAS.
URBAN (1)	86.7	6.7	2.4		4.3
AGRICULTURE (2)	19.0	76.2	4.8		
FOREST (4)	5.9	2.9	91.2		
WATER (5)	7.5		2.5	65.0	25.0

LEVEL II LAND USE* 7 Channels, 7 Bits, 30 Meters

GROUND TRUTH	AGGREGATED COMPUTER SPECTRAL CLASSES						
	RES	COM/IND	AG	PAST	FOR	WATER	UNCLAS.
RESIDENTIAL (11)	61.1	24.2	6.3	.6	3.8		2.5
COMMERCIAL/ INDUSTRIAL (12/13)	28.6	60.2	4.1	2.0			5.1
CROPLAND (21)	26.6		46.7	20.0	6.7		
PASTURE (22)	14.8		14.8	66.7	3.7		
FOREST Deciduous (41)	5.9			2.9	91.2		
WATER (50)		7.5			2.5	65.0	25.0

*ANDERSON LAND USE CLASSES ARE SHOWN IN PARENTHESES

TABLE A-20. PERFORMANCE MATRIX, BALTIMORE, MARYLAND

LEVEL III COMPUTER SPECTRAL CLASSIFICATION OF LAND USE   7 Channels, 7 Bits, 30 Meters

GROUND TRUTH	FAM Single Family Res. (111)	APT1 APT2 Multiple Family (112)	RLR SOIL ASPH Commercial (121/122)	HDR DR Industrial (130)	SOIL CROP Cropland (210)	PASTURE Pasture (220)	FOREST Deciduous Forest (410)	Water (500)	Unclassified
Single Family Residential (111)	52.0	20.0	1.2	5.3	9.3		6.7		5.3
Multi-family (112) and Institutional (160)	19.5	31.7	13.5	26.8	3.6	1.2	1.2		2.4
Commercial (121/122)	7.8	21.6	35.3	27.4	2.0	2.0			3.9
Industrial (13)	4.3	23.4	44.7	12.8	6.4	2.1			6.4
Cropland (210)	20.0	6.7			46.7	20.0	6.7		
Pasture (220)	3.7	11.1			14.8	66.7	3.7		
Deciduous Forest (410)	5.9					2.9	91.2		
Water (500)			2.5	5.0			2.5	65.0	25.0

State of Maryland Land Use Classes are shown in parentheses.

TABLE A-21. PERFORMANCE MATRICES

BALTIMORE LAND USE - AVERAGE ACCURACY
(WEIGHTED) FOR GAIN VARIATIONS
(30 METER DATA, 7 OPTIMUM CHANNELS)

-1/3 Gain	% CORRECT	% ERRORS	
		Commission	Omission
LEVEL I	59.7	15.4	24.9
LEVEL II	41.6	33.5	24.9
LEVEL III	25.1	50.0	24.9

+1/3 Gain	% CORRECT	% ERRORS	
		Commission	Omission
LEVEL I	73.2	17.3	9.5
LEVEL II	57.3	33.2	9.5
LEVEL III	42.7	47.8	9.5

TABLE A-22. PERFORMANCE MATRICES

BALTIMORE LAND USE - AVERAGE ACCURACY
(WEIGHTED) FOR GAIN VARIATIONS
(30 METER DATA, 7 OPTIMUM CHANNELS)

-2/3 Gain	% CORRECT	% ERRORS	
		Commission	Omission
LEVEL I	6.5	5.7	87.9
LEVEL II	5.4	6.7	87.9
LEVEL III	1.4	10.8	87.9

+2/3 Gain	% CORRECT	% ERRORS	
		Commission	Omission
LEVEL I	61.7	25.3	12.9
LEVEL II	44.5	42.6	12.9
LEVEL III	31.0	56.1	12.9

TABLE A-23 PERFORMANCE MATRICES
BALTIMORE LAND USE

LEVEL I LAND USE* 7 Channels, +1/3 Gain, 30 Meter Data

AGGREGATED COMPUTER SPECTRAL CLASSES

GROUND TRUTH	URBAN	AG	FOREST	WATER	UNCLAS.
URBAN (1)	84.3	5.1	7.1		3.5
AGRICULTURE (2)	14.6	26.8	56.1		2.4
FOREST (4)	2.9		97.1		
WATER (5)	5.0		2.5	30.0	62.5

LEVEL II LAND USE* 7 Channels, +1/3 Gain, 30 Meter Data

AGGREGATED COMPUTER SPECTRAL CLASSES

GROUND TRUTH	RES	COM/ IND	AG	PAST	FOR	WATER	UNCLAS.
RESIDENTIAL (11)	72.0	10.2	4.5	0.6	10.2		2.6
COMMERCIAL/ INDUSTRIAL (12/13)	41.8	45.9	4.1	1.0	2.0		5.1
CROPLAND (21)	21.4		7.1		71.4		
PASTURE (22)	11.1		7.4	29.6	48.2		3.7
FOREST Deciduous (41)	2.9				97.1		
WATER (50)	2.5	2.5			2.5	30.0	62.5

*ANDERSON LAND USE CLASSES ARE SHOWN IN PARENTHESES

TABLE A-24. PERFORMANCE MATRIX, BALTIMORE, MARYLAND

LEVEL III COMPUTER SPECTRAL CLASSIFICATION OF LAND USE 7 Channels, + 1/3 Gain, 30 Meters

GROUND TRUTH	FAM Single Family Res. (111)	APT1 APT2 Multiple Family (112)	RLR SOIL ASPH Commercial (121/122)	MDR DR Industrial (130)	SOIL CROP Cropland (210)	PASTURE Pasture (220)	FOREST Deciduous Forest (410)	Water (500)	Unclassified
Single Family Residential (111)	40.0	30.7	1.3		8.0	1.3	16.0		2.7
Multi-family (112) and Institutional (160)	9.8	63.4	8.5	9.8	1.2		4.9		2.4
Commercial (121/122)	7.8	49.0	23.5	13.7	2.0		2.0		2.0
Industrial (13)	2.1	23.4	34.1	21.3	6.4	2.1	2.1		8.5
Cropland (210)	14.3	7.1			7.1		71.4		
Pasture (220)	3.7	7.4			7.4	29.6	48.2		3.7
Deciduous Forest (410)	3.0						97.0		
Water (500)		2.5		2.5			2.5	30.0	62.5

State of Maryland Land Use Classes are in parentheses.

TABLE A-25 PERFORMANCE MATRICES

BALTIMORE LAND USE

LEVEL I LAND USE* 7 Channels, -1/3 Gain, 30 Meter Data

GROUND TRUTH	AGGREGATED COMPUTER SPECTRAL CLASSES				
	URBAN	AG	FOREST	WATER	UNCLAS.
URBAN (1)	73.3	8.2			18.4
AGRICULTURE (2)	14.3	59.5			26.2
FOREST (4)	30.3	48.5	18.2		3.0
WATER (5)	10.0			7.5	82.5

LEVEL II LAND USE* 7 Channels, - 1/3 Gain, 30 Meter Data

GROUND TRUTH	AGGREGATED COMPUTER SPECTRAL CLASSES						
	RES	COM/ IND	AG	PAST	FOR	WATER	UNCLAS.
RESIDENTIAL (11)	47.8	24.8	6.4	3.8			17.2
COMMERCIAL/ INDUSTRIAL (12/13)	23.5	51.0	4.1	1.0			20.4
CROPLAND (21)	13.3		13.3	26.7			46.7
PASTURE (22)	11.1	3.7	3.7	66.7			14.8
FOREST Deciduous (41)	30.3		30.3	18.2	18.2		3.0
WATER (50)	5.0	5.0				7.5	82.5

*ANDERSON LAND USE CLASSES ARE SHOWN IN PARENTHESES

TABLE A-26. PERFORMANCE MATRIX, BALTIMORE, MARYLAND

LEVEL III COMPUTER SPECTRAL CLASSIFICATION OF LAND USE 7 Channels, -1/3 Gain, 30 Meters

GROUND TRUTH	FAM Single Family Res. (111)	APT1 APT2 Multiple Family (112)	RLR SOIL ASPH Commercial (121/122)	MDR DR Industrial (130)	SOIL CROP Cropland (210)	PASTURE Pasture (220)	FOREST Deciduous Forest (410)	Water (500)	Unclassified
Single Family Residential (111)	28.0	33.3	1.3	2.7	12.0	4.0			13.7
Multi-family (112) and Institutional (160)	4.9	30.5	15.9	28.1	1.2	3.7			15.9
Commercial (121/122)	5.9	19.6	27.5	21.6	2.0	2.0			21.6
Industrial (13)	4.3	17.0	44.7	8.5	6.4				19.2
Cropland (210)	6.7	6.7			13.3	26.7			46.7
Pasture (220)	3.7	7.4	3.7		3.7	66.7			14.8
Deciduous Forest (410)	30.3				30.3	18.2	18.2		3.0
Water (500)	5.0		2.5	2.5				7.5	82.5

State of Maryland Land Use Classes are shown in parentheses

TABLE A-27. PERFORMANCE MATRICES

BALTIMORE LAND USE

LEVEL I LAND USE* 7 Channels, +2/3 Gain, 30 Meter Data

AGGREGATED COMPUTER SPECTRAL CLASSES

GROUND TRUTH	URBAN	AG	FOREST	WATER	UNCLAS.
URBAN (1)	72.9	3.1	16.9		7.1
AGRICULTURE (2)	14.3	2.4	83.3		
FOREST (4)			100.0		
WATER (5)	2.5		2.5	20.0	75.0

LEVEL II LAND USE* 7 Optimum Channels, +2/3 Gain, 30 Meter Data

AGGREGATED COMPUTER SPECTRAL CLASSES

GROUND TRUTH	RES	COM/ IND	AG	PAST	FOR	WATER	UNCLAS.
RESIDENTIAL (11)	51.0	17.2	2.6		22.9		6.4
COMMERCIAL/ INDUSTRIAL (12/13)	37.8	42.9	4.1		7.1		8.2
CROPLAND (21)	6.7				93.3		
PASTURE (22)	18.5			3.7	77.8		
FOREST Deciduous (41)					100.0		
WATER (50)	2.5					20.0	75.0

*ANDERSON LAND USE CLASSES ARE SHOWN IN PARENTHESES

TABLE A-28. PERFORMANCE MATRIX, BALTIMORE, MARYLAND

LEVEL III COMPUTER SPECTRAL CLASSIFICATION OF LAND USE 7 Channels, + 2/3 Gain, 30 Meters

GROUND TRUTH	FAM Single Family Res. (111)	APT1 APT2 Multiple Family (112)	RLR SOIL ASPH Commercial (121/122)	MDR DR Industrial (130)	SOIL CROP Cropland (210)	PASTURE Pasture (220)	FOREST Deciduous Forest (410)	Water (500)	Unclassified
Single Family Residential (111)	17.3	28.0	2.7	2.7	4.0		36.0		9.3
Multi-family (112) and Institutional (160)	8.5	47.6	9.8	18.3	1.2		11.0		3.7
Commercial (121/122)	3.9	41.2	19.6	17.7	2.0		9.8		5.9
Industrial (13)	4.3	25.5	27.6	21.3	6.4		4.3		10.6
Cropland (210)		6.7					93.3		
Pasture (220)	7.4	11.1				3.7	77.8		
Deciduous Forest (410)							100.0		
Water (500)		2.5					2.5	20	75.0

State of Maryland Land Use Classes are in parentheses.

TABLE A-29. PERFORMANCE MATRICES

BALTIMORE LAND USE

LEVEL I LAND USE* 7 Channels, -2/3 Gain, 30 Meter Data

GROUND TRUTH	AGGREGATED COMPUTER SPECTRAL CLASSES: URBAN	AG	FOREST	WATER	UNCLAS.
URBAN (1)	9.4	2.4			88.2
AGRICULTURE (2)					100.0
FOREST (4)	11.8	26.5			61.8
WATER (5)	5.0				95.0

LEVEL II LAND USE* 7 Channels, -2/3 Gain, 30 Meter Data

GROUND TRUTH	AGGREGATED COMPUTER SPECTRAL CLASSES: RES	COM/IND	AG	PAST	FOR	WATER	UNCLAS.
RESIDENTIAL (11)	7.0	1.3	1.9				89.8
COMMERCIAL/ INDUSTRIAL (12/13)	2.0	9.2	3.1				85.7
CROPLAND (21)							100.0
PASTURE (22)							100.0
FOREST Deciduous (41)	11.8			26.5			61.8
WATER (50)	5.0						95.0

*ANDERSON LAND USE CLASSES ARE SHOWN IN PARENTHESES

TABLE A-30. PERFORMANCE MATRIX, BALTIMORE, MARYLAND

LEVEL III COMPUTER SPECTRAL CLASSIFICATION OF LAND USE 7 Channels, -2/3 Gain, 30 Meters

GROUND TRUTH	FAM Single Family Res. (111)	APT1 APT2 Multiple Family (112)	RLR SOIL ASPH Commercial (121/122)	MDR DR Industrial (130)	SOIL CROP Cropland (2[illegible])	PASTURE Pasture (220)	FOREST Deciduous Forest (410)	Water (500)	Unclassified
Single Family Residential (111)		10.7			4.0				85.3
Multi-family (112) and Institutional (160)		3.7	2.4						93.9
Commercial (121/122)	2.0				2.0				96.0
Industrial (13)		2.1	14.9	4.3	4.3				74.5
Cropland (210)									100
Pasture (220)									100
Deciduous Forest (410)	8.8	3.0				26.5			61.8
Water (500)	5.0								95.0

State of Maryland Land Use Classes are shown in parentheses

TABLE A-31. PERFORMANCE MATRICES

BALTIMORE LAND USE - AVERAGE ACCURACY (WEIGHTED) FOR OFFSET VARIATIONS (30 METER DATA, 7 OPTIMUM CHANNELS)

+1/3 Offset	% CORRECT	% ERRORS	
		Commission	Omission
LEVEL I	12.9	15.7	71.4
LEVEL II	9.7	18.9	71.4
LEVEL III	7.3	21.3	71.4

-1/3 Offset	% CORRECT	% ERRORS	
		Commission	Omission
LEVEL I	55.5	20.2	24.3
LEVEL II	42.6	33.1	24.3
LEVEL III	21.0	54.7	24.3

TABLE A-32. PERFORMANCE MATRICES

BALTIMORE LAND USE - AVERAGE ACCURACY (WEIGHTED) FOR OFFSET VARIATIONS (30 METER DATA, 7 OPTIMUM CHANNELS)

+2/3 Offset	% CORRECT	% ERRORS	
		Commission	Omission
LEVEL I	0.0	3.2	96.8
LEVEL II	0.0	3.2	96.8
LEVEL III	0.0	3.2	96.8

-2/3 Offset	% CORRECT	% ERRORS	
		Commission	Omission
LEVEL I	8.0	3.9	88.1
LEVEL II	6.4	5.5	88.1
LEVEL III	0.8	11.1	88.1

TABLE A-33. PERFORMANCE MATRICES

BALTIMORE LAND USE

LEVEL I LAND USE* 7 Channels, +1/3 Offset, 30 Meter Data

GROUND TRUTH	AGGREGATED COMPUTER SPECTRAL CLASSES				
	URBAN	AG	FOREST	WATER	UNCLAS.
URBAN (1)	13.7		9.8	0.4	76.1
AGRICULTURE (2)		7.1	76.2		16.7
FOREST (4)			29.4		70.6
WATER (5)					100.0

LEVEL II LAND USE* 7 Channels, +1/3 Offset, 30 Meter Data

GROUND TRUTH	AGGREGATED COMPUTER SPECTRAL CLASSES						
	RES	COM/ IND	AG	PAST	FOR	WATER	UNCLAS.
RESIDENTIAL (11)	9.6	1.9			14.7		73.9
COMMERCIAL/ INDUSTRIAL (12/13)	9.2	8.2			2.0	1.0	79.6
CROPLAND (21)					73.3		26.7
PASTURE (22)				11.1	77.8		11.1
FOREST Deciduous (41)					29.4		70.6
WATER (50)							100.0

*ANDERSON LAND USE CLASSES ARE SHOWN IN PARENTHESES

TABLE A-34. PERFORMANCE MATRIX, BALTIMORE, MARYLAND

LEVEL III COMPUTER SPECTRAL CLASSIFICATION OF LAND USE 7 Channels, + 1/3 Offset, 30 Meters

GROUND TRUTH	FAM Single Family Res. (111)	APT1 APT2 Multiple Family (112)	RLR SOIL ASPH Commercial (121/122)	MDR DR Industrial (130)	SOIL CROP Cropland (210)	PASTURE Pasture (220)	FOREST Deciduous Forest (410)	Water (500)	Unclassified
Single Family Residential (111)	2.7	2.7	1.3				21.3		72.0
Multi-family (112) and Institutional (160)	1.2	12.2	2.4				8.5		75.6
Commercial (121/122)	3.9	7.8	3.9				2.0		82.4
Industrial (13)		6.4	12.8				2.1	2.1	76.6
Cropland (210)							73.3		26.7
Pasture (220)						11.1	77.8		11.1
Deciduous Forest (410)							29.4		70.6
Water (500)									100

State of Maryland Land Use Classes are shown in parentheses

TABLE A-35. PERFORMANCE MATRICES

BALTIMORE LAND USE

LEVEL I LAND USE* 7 Channels, -1/3 Offset, 30 Meter Data

GROUND TRUTH	AGGREGATED COMPUTER SPECTRAL CLASSES				
	URBAN	AG	FOREST	WATER	UNCLAS.
URBAN (1)	70.4	5.5			24.1
AGRICULTURE (2)	35.7	54.8			9.5
FOREST (4)	67.7	32.4			
WATER (5)	25.0			12.5	62.5

LEVEL II LAND USE* 7 Channels, -1/3 Offset, 30 Meter Data

GROUND TRUTH	AGGREGATED COMPUTER SPECTRAL CLASSES						
	RES	COM/IND	AG	PAST	FOR	WATER	UNCLAS.
RESIDENTIAL (11)	52.2	15.9	5.1	1.9			24.8
COMMERCIAL/ INDUSTRIAL (12/13)	18.8	55.2	1.0	2.1			22.9
CROPLAND (21)	46.7			33.3			20.0
PASTURE (22)	25.9	3.7		66.7			3.7
FOREST Deciduous (41)	67.7		14.7	17.7			
WATER (50)	7.5	17.5				12.5	62.5

*ANDERSON LAND USE CLASSES ARE SHOWN IN PARENTHESES

TABLE A-36. PERFORMANCE MATRIX, BALTIMORE, MARYLAND

LEVEL III COMPUTER SPECTRAL CLASSIFICATION OF LAND USE 7 Channels, -1/3 Offset, 30 Meters

	FAM	APT1 APT2	RLR SOIL ASPH	MDR DR	SOIL CROP	PASTURE	FOREST		
GROUND TRUTH	Single Family Res. (111)	Multiple Family (112)	Commercial (121/122)	Industrial (130)	Cropland (210)	Pasture (220)	Deciduous Forest (410)	Water (500)	Unclassified
Single Family Residential (111)	8.0	61.3	2.7		9.3	2.7			16.0
Multi-family (112) and Institutional (160)	2.4	34.2	26.8	1.2	1.2	1.2			32.9
Commercial (121/122)	2.0	21.6	39.2	3.9	2.0	3.9			27.5
Industrial (13)		13.3	66.7	2.2					17.8
Cropland (210)	13.3	33.3				33.3			20.0
Pasture (220)	7.4	18.5	3.7			66.7			3.7
Deciduous Forest (410)	61.8	5.9			14.7	17.7			
Water (500)	7.5		5.0	12.5				12.5	62.5

State of Maryland Land Use Classes are shown in parentheses.

TABLE A-37. PERFORMANCE MATRICES

BALTIMORE LAND USE

LEVEL I LAND USE* 7 Channels, +2/3 Offset, 30 Meter Data

GROUND TRUTH	AGGREGATED COMPUTER SPECTRAL CLASSES				
	URBAN	AG	FOREST	WATER	UNCLAS.
URBAN (1)		4.7			95.3
AGRICULTURE (2)					100.0
FOREST (4)					100.0
WATER (5)					100.0

LEVEL II LAND USE* 7 Channels, +2/3 Offset, 30 Meter Data

GROUND TRUTH	AGGREGATED COMPUTER SPECTRAL CLASSES						
	RES	COM/ IND	AG	PAST	FOR	WATER	UNCLAS.
RESIDENTIAL (11)			4.5				95.5
COMMERCIAL/ INDUSTRIAL (12/13)			5.1				94.9
CROPLAND (21)							100.0
PASTURE (22)							100.0
FOREST Deciduous (41)							100.0
WATER (50)							100.0

*ANDERSON LAND USE CLASSES ARE SHOWN IN PARENTHESES

TABLE A-38. PERFORMANCE MATRIX, BALTIMORE, MARYLAND

LEVEL III COMPUTER SPECTRAL CLASSIFICATION OF LAND USE 7 Channels, + 2/3 Offset, 30 Meters

GROUND TRUTH	FAM Single Family Res. (111)	APT1 APT2 Multiple Family (112)	RLR SOIL ASPH Commercial (121/122)	MDR DR Industrial (130)	SOIL CROP Cropland (210)	PASTURE Pasture (220)	FOREST Deciduous Forest (410)	Water (500)	Unclassified
Single Family Residential (111)					6.7				93.3
Multi-family (112) and Institutional (160)					2.4				97.6
Commercial (121/122)					2.0				98.0
Industrial (13)					8.5				91.5
Cropland (210)									100.0
Pasture (220)									100.0
Deciduous Forest (410)									100.0
Water (500)									100.0

TABLE A-39. PERFORMANCE MATRICES

BALTIMORE LAND USE

LEVEL I LAND USE* 7 Channels, -2/3 Offset, 30 Meter Data

GROUND TRUTH	AGGREGATED COMPUTER SPECTRAL CLASSES				
	URBAN	AG	FOREST	WATER	UNCLAS.
URBAN (1)	11.4				88.6
AGRICULTURE (2)	2.4	2.4			95.2
FOREST (4)	23.5	2.9			73.5
WATER (5)	10.0				90.0

LEVEL II LAND USE* 7 Channels, -2/3 Offset, 30 Meter Data

GROUND TRUTH	AGGREGATED COMPUTER SPECTRAL CLASSES						
	RES	COM/IND	AG	PAST	FOR	WATER	UNCLAS.
RESIDENTIAL (11)	3.8	3.8					92.4
COMMERCIAL/ INDUSTRIAL (12/13)		17.4					82.7
CROPLAND (21)	6.7		6.7				86.7
PASTURE (22)							100.0
FOREST Deciduous (41)	23.5			2.9			73.5
WATER (50)	2.5	7.5					90.0

*ANDERSON LAND USE CLASSES ARE SHOWN IN PARENTHESES

TABLE A-40. PERFORMANCE MATRIX, BALTIMORE, MARYLAND

LEVEL III COMPUTER SPECTRAL CLASSIFICATION OF LAND USE 7 Channels, -2/3 Offset, 30 Meters

GROUND TRUTH	FAM Single Family Res. (111)	APT1 APT2 Multiple Family (112)	RLR SOIL ASPH Commercial (121/122)	MDR DR Industrial (130)	SOIL CROP Cropland (210)	PASTURE Pasture (220)	FOREST Deciduous Forest (410)	Water (500)	Unclassified
Single Family Residential (111)		8.0	2.7						89.3
Multi-family (112) and Institutional (160)			4.9						95.1
Commercial (121/122)			2.0						98.0
Industrial (13)			31.9	2.1					66.0
Cropland (210)		6.7			6.7				86.7
Pasture (220)									100.0
Deciduous Forest (410)		23.5				2.9			73.5
Water (500)		2.5		7.5					90.0

State of Maryland Land Use Classes are shown in parentheses

APPENDIX B

ADDITIONAL DETAILS OF AGRICULTURAL RECOGNITION RESULTS
MICHIGAN AGRICULTURE

ADDITIONAL DETAILS OF AGRICULTURAL RECOGNITION RESULTS

The makeup and spectral separability of classes and their relative importance to the user are key factors that must be considered whenever recognition processing results are evaluated. Another key point is the quality and nature of ground truth information. The labels assigned to fields frequently are too broad or not sufficiently descriptive to indicate the full variability present in the scene.

Major crops which tend to be uniformly planted are better described by a single label, like "corn", than are other agricultural areas like pastures. Even in major crops there can be substantial differences in percent cover and crop condition, among other differences. The 1973 growing season in Michigan was unusual in that excessive rain and wetness in fields delayed some plantings by several weeks, five weeks for one particular corn field. As a consequence, it was found necessary to define separate signatures for both dense and sparse corn. Differences between individual fields of other types, for example, pastures, harvested fields, and idle or fallow fields, can be much larger than for major crops, depending on level of use and recent management practices. The effort required to collect good ground truth information is too often underestimated. The ground truth available for the agricultural data set in this study was among the best we have ever utilized, but even so, it had not been practical to visit every field on the ground and describe all characteristics of these fields. Photointerpretation and Agricultural Stabilization and Conservation Service (ASCS) records were utilized to supplement ground visits.

If members of two or more relatively unimportant classes are frequently confused or if one or more unimportant classes is poorly recognized, a misleading assessment might be made of overall recognition performance. The agricultural data set discussed in the main body of this report is a case in point.

Results are presented in the main body for five recognition classes: corn, soybeans, oats, woods, and other. The first four are the significant crops for the test area, while the last includes everything else in the scene, including points not assigned to any recognition signature because of their distance from them (i.e., the low likelihood that these points belonged to any one of the signature distributions). Four distinct signatures were determined and used to represent the "other" class; these are bare soil, stubble/cut hay, pasture/grasses, and dense green vegetation.

Initially, results were tallied and reported separately for each of the four major classes and the four "other" subclasses (five with the not-recognized subclass). These initial results were subjected to extensive analysis which is reported in this appendix. Particular attention is paid to confusion among the "other" subclasses. Nevertheless, it is believed that the five-class results of the main body represents the more appropriate and pertinent picture of recognition performance for this study.

By way of illustration before discussing the eight-class results, an example of differences between eight and five-class performance summaries is appropriate. Table B-1 presents eight-class results for 15 m data with seven optimum spectral channels. A weighted class average of 75.1 percent correct was achieved, ranging from 31.6 percent to 100 percent. The corresponding five-class performance summary, Table B-2, shows an overall class average of 86.5 percent correct, with a low of 59.9 percent for soybeans. Thus, it can be seen that one might reach substantially different conclusions about recognition performance, depending upon which performance summary was examined.

B.1 ANALYSIS OF 15-M AGRICULTURAL RECOGNITION RESULTS

Results for agricultural data with 15 m resolution already have been presented (Table B-1) for eight recognition classes. An exami-

TABLE B-1. SAMPLE EIGHT-CLASS RECOGNITION PERFORMANCE SUMMARY
7-Channel Data, 15-m Spatial Resolution

15 METER DATA - 7 OPTIMUM CHANNELS

		PER CENT MISCLASSIFICATION								
SCENE CLASS (No. of Pixels)	% CORRECT CLASS.	BARE SOIL	CORN	SOY-BEANS	STUBBLE CUT HAY	RIPE OATS	PASTURE GRASSES	DENSE GREEN	WOODS	UNCLAS.
BARE SOIL (736)	76.8			2.3	1.2	0.1				19.6
CORN (3248)	94.6			0.1	0.2		0.4	3.8	0.8	0.2
SOYBEANS (1136)	59.9	2.3	14.3		0.7			19.4		3.4
STUBBLE CUT HAY (1648)	36.0	44.3	2.2	0.4		5.8	8.4	0.5	0.5	1.9
RIPE OATS (80)	100.0									
PASTURE-GRASSES (864)	31.6		18.1		22.1	0.6		15.4	10.2	2.1
DENSE GREEN (1424)	62.5		22.7	0.1					11.9	2.9
WOODS (3440)	95.5		2.8	0.1			0.1	1.3		0.3

Weighted Average Correct Classification = 75.1%

TABLE B-2. SAMPLE FIVE-CLASS RECOGNITION PERFORMANCE SUMMARY, CORRESPONDING TO TABLE B-1

15 METER DATA - 7 OPTIMUM CHANNELS		PER CENT MISCLASSIFICATION				
SCENE CLASS (No. of Pixels)	PER CENT CORRECT CLASSIFICATION	CORN	SOY-BEANS	RIPE OATS	WOODS	OTHER
CORN (3248)	94.6		0.1		0.8	4.5
SOYBEANS (1136)	59.9	14.3	0.1			25.8
RIPE OATS (80)	100.0					
WOODS (3440)	95.5	2.8	0.1			1.6
OTHER (4672)	80.6	11.0	0.5	2.1	5.5	

Wt. Average = 86.5%

nation on large-scale aerial photographs was made of each test field in which a large number of pixels were either misclassified or not recognized. The following paragraphs summarize results for each class of ground cover, giving explanations for patterns of misclassification where possible.

Bare Soil

The major problem with this class was the number of not-recognized pixels, which amounted to almost 20 percent of the test set. Fields with substantial amounts of not-recognized points contained dark soil in patterns similar to the patterns of non-classification. Dark bare soil was not used as a training set, hence this non-classification is logical. Occasional weedy patches were called soybeans.

Corn

Corn was in general well recognized. However, almost 4 percent of the points were misclassified as dense green. The points so classified proved to be weedy patches in the corners or along the edges of corn fields. Occasional bare spots in corn fields were not classified.

Soybeans

Recognition of this class showed great variability from field to field as a result of variation in percentage cover of the soybeans at this time of year, and because of the presence of weedy patches always found in soybeans. The soybean training set was selected from fields having uniform and high cover. Even so, the soybean signature was similar to the dense green signature and problems of misclassification between these two classes were anticipated.

In general, dense stands of soybeans were correctly classified. Weedy dense stands were called dense green. Sparse stands were called

sparse corn, accounting for the large fraction of test set called corn. Some very sparse areas were called bare soil. Occasional areas of sparse cover with dark soil backgrounds were not recognized.

The general problem with accurate soybean recognition seems to be the great variation in percentage cover at this time in the growing season (the date of data collection was 5 August, in a late growing season which means not all plants were fully mature) and the presence of weedy patches in fields.

Stubble/Cut Hay

This was another spectrally variable, poorly recognized category. The training set included stubble fields with little or no green weed growth and some dead stalks showing the false-color infrared (CIR) photography. The major misclassification were bare soil, ripe oats, pastures, and a little corn.

Areas where the straw had been gathered appeared like bare soil and were so classified. Areas where there was considerable weed growth (or a leguminous cover crop, which frequently is planted in stubble fields following wheat harvest) were called pastures. A few exceedingly dense spots were called corn.

The cause of low recognition accuracy of this class was the extreme spectral variability of stubble fields at this time of year. Depending on field treatment, this class could look very much like oats (non-harvested or lodged areas), stubble, bare soil (straw gathered), or pasture (leguminous understory developed).

Ripe Oats

Test fields were perfectly classified. At this time of year, oats were fairly uniformly yellow in color. They were harvested one week after MSS data collection, which was about one month later than usual.

Pasture/Grasses

This class was poorly recognized, probably because of the great spectral variability in the class. The training set included areas of medium vegetation cover, with some bare soil apparent from the tone on the CIR photography. Major misclassifications occurred as corn, stubble, dense green, and woods. General comments are given below, while a more detailed analysis of pasture recognition is presented in Section B.3.

Corn recognition occurred in three of the nine original pasture test fields. When inspected on large-scale (1:2000) low-altitude black-and-white photography, one of these fields (64) exhibited a row structure which identified it as actually being corn, so it was deleted from the pasture class. The other two fields where substantial corn misclassification occurred were in very lush and obviously ungrazed areas.

Stubble recognition occurred in pasture areas which were unusually sparse — bare soil was visible in the CIR photography. In view of what has already been said about the stubble training set, these results seem plausible.

Dense green recognition occurred in areas of pasture which were lush, but not as lush as those areas called corn. There was a definite difference in the red color of CIR photography between pasture areas called corn, dense green, and pasture, although the signatures for dense green, pasture, stubble, and bare soil represent a continuum of percentage grass vegetation cover-from large percentage cover (dense green) to no cover (bare soil). One would logically expect spectrally variable areas such as pasture to exhibit some recognition from each of these categories.

A few scattered trees in pasture areas were called woods.

Dense Green

This class, as noted above, represents dense green vegetation (or alfalfa) growing in fields. The major misclassifications in dense green fields were corn and woods.

Corn recognition occurred in the more sparse areas of the dense green test set. These points were recognized by the sparse corn signature. Woods recognition occurred occasionally, scattered through fields. Some, but not all, of the woods misclassification can be explained by trees in fields; the rest seem to be genuine misclassifications.

Woods

Woods in this area are mainly oak-hickory hardwood forests with varying percentage cover. The only misclassification of significance here was corn. That occurred in one sparse woods area in the corner of one of the test set fields. Dense green recognition also was observed there.

Summary

Corn, ripe oats, and woods were well recognized. Soybean recognition was low because of misclassifications as dense green vegetation and corn, resulting from variations in percent ground cover and the presence of weeds. Bare soil recognition was reduced by a failure to train on and recognize dark soil areas. Stubble and pastures exhibited substantial spectral variability and consequent misclassification, while sparser areas of dense green vegetation were misclassified.

B.2 COMPARISON OF 15 M, 30M, AND 60 M RECOGNITION RESULTS

Eight-class recognition results for spatial resolutions of 30 m and 60 m are presented in Tables B-3 and B-4, respectively. They were compared with Table B-1 for detection of trends in recognition accuracy

TABLE B-3. FIELD CENTER CLASSIFICATION ACCURACIES
7 CHANNEL DATA, NOMINAL 30-M SPATIAL RESOLUTION

30 METER DATA - 7 OPTIMUM CHANNELS		PER CENT MISCLASSIFICATION								
SCENE (No. of CLASS Pixels)	% CORRECT CLASS.	BARE SOIL	CORN	SOY-BEANS	STUBBLE CUT HAY	RIPE OATS	PASTURE GRASSES	DENSE GREEN	WOODS	UNCLAS.
BARE SOIL (184)	87.0				0.5					12.5
CORN (812)	94.1				0.7		0.1	3.9	0.7	0.4
SOYBEANS (28[illegible])	73.9	3.2	5.3					13.0		4.6
STUBBLE CUT HAY (412)	37.4	51.7	1.2	0.7		2.9	2.7	0.2	1.2	1.9
RIPE OATS (20)	100.0									
PASTURE-GRASSES (216)	33.8	0.9	14.4		17.1			13.4	13.4	6.9
DENSE GREEN (356)	70.8		21.1	0.6			0.3		4.5	2.8
WOODS (860)	96.7		1.9				0.1	1.0		0.2

Weighted Average Correct Classification = 78.4%

TABLE B-4. FIELD CENTER CLASSIFICATION ACCURACIES
7 CHANNEL DATA, NOMINAL 60-M SPATIAL RESOLUTION

60 METER DATA - 7 OPTIMUM CHANNELS		PER CENT MISCLASSIFICATION								
SCENE CLASS (No. of Pixels)	% CORRECT CLASS.	BARE SOIL	CORN	SOY-BEANS	STUBBLE CUT HAY	RIPE OATS	PASTURE GRASSES	DENSE GREEN	WOODS	UNCLAS.
BARE SOIL (46)	84.8									15.2
CORN (203)	93.6			0.5				3.9	0.5	1.5
SOYBEANS (71)	29.6		29.6					38.0		2.8
STUBBLE CUT HAY (103)	46.6	37.9	1.0			2.9				12.6
RIPE OATS (5)	100.0									
PASTURE-GRASSES (54)	24.1		18.5		14.8	9.3		13.0	7.4	13.0
DENSE GREEN (89)	77.5		15.7		1.1				1.1	4.5
WOODS (215)	97.7		1.9					0.5		

Weighted Average Correct Classification = 75.7%

when spatial resolution was degraded from 15 to 30 to 60 m. Again, performance in each of the test fields was examined and related to the pattern of errors previously discussed in Section B.1.

Bare Soil

The major factor influencing the recognition accuracy for bare soil (as resolution was varied) was the not-recognized class. At 15 m, 3.6 percent of areas were misclassified, while 19.6 percent of points were not classified for reasons discussed before. At 30 and 60 m resolution, the small weedy patches were averaged with other bare soil points so that misclassification disappeared.

The test for the not-recognized class is based on the sizes of signature standard deviations (a χ^2 test is used). Since signature standard deviations decrease in going from 15 to 30 to 60 m resolution, one could expect more pixels to be not classified at the larger resolutions. However, this effect was offset here to an extent by the averaging of dark bare soil pixels with light bare soil pixels at boundaries — these boundary areas being subsequently called bare soil. This averaging caused the not-classified category to be smaller at 30 m than at 15 m. Correct soil recognition increased, but centers of dark bare soil areas still were not recognized. At 60 m, where fields of 4 to 8 pixels were common and only 46 pixels were tested for bare soil, a one pixel shift between categories is sufficient to shift results by 2 percent; bare soil recognition decreased by that amount from the percentage for 30 m, while the not-recognized category increased about the same.

Corn

The recognition accuracy of corn remained nearly constant as a function of spatial resolution. Only a slight increase in the size of the not-classified category was observed in going from 15 to 60 m,

and misclassifications as dense green and woods remained substantially constant.

Soybeans

Major changes occurred in the accuracy and pattern of misclassifications in the soybeans data. Qualitatively, this was caused by the spectral variability of soybeans and a typical field mottling pattern at a scale of 30 to 60 m observed on the photos. This point will be elaborated below.

In going from 15 to 30 m resolution, there was a major decrease in corn and dense green misclassification. Bare soil misclassification decreased slightly, while the not-classified category increased slightly.

Bare soil misclassification occurred in the same two fields in the 30 m data as in the 15 m data, but at a reduced percentage of the total area. Bare spots were fairly small and localized (even though the percentage cover in the fields where bare soil recognition occurred was generally low and variable). In generation of the coarser resolution data, pixels along edges of the bare soil areas were averaged with soybean pixels to produce composite pixels recognized as soybeans in the 30 m data.

Major decreases in false corn recognition occurred in two of the three soybean fields when going from 15 to 30 m resolution. Many pixels called sparse corn on the 15 m data were called soybeans on the 30 m data.

In comparing the standard deviations and means of the sparse corn and soybean signatures at 15 and 30 m, we find that standard deviations for corn at 30 m are about 91 percent of those at 15 m, while soybean standard deviations at 30 m are 98 percent of those at 15 m. The effect of the reduction in standard deviations is magnified by the fact that in six of the seven channels used for recognition, the

mean separation between soybeans and sparse corn is less than one standard deviation of soybeans. These changes could cause a shift of the decision boundary between sparse corn and soybeans so as to favor soybean recognition.

The same explanation holds for the decrease in dense green recognition, although the dense green spots were generally small and would tend to be averaged with more normal soybeans points and be called soybeans. Examination of the recognition maps for 30 m and 15 m data reveals that dense green points on the 15 m map are averaged with points called soybeans on the map. The result is called soybeans on the 30 m map, resulting in a decrease in misclassification of soybeans as dense green.

When going from 30 m to 60 m data, the dramatic decrease in the classification accuracy of soybeans is caused by the rather solid misclassification of two of the four test fields as sparse corn and as dense green. There also was substantial recognition of sparse corn and dense green in these fields at 15 m resolution.

Stubble

The major effect on stubble recognition in going from 15 to 60 m was a decrease in misclassification as bare soil and an increase of the not-classified category. Compared with 15 m data, misclassifications as corn, dense green, pastures, and soybeans all decreased as resolution element size was increased, because the previously misclassified areas were small and were averaged with pixels normally called stubble.

Increases in the not-recognized category occurred in three fields at 60 m resolution. In one field, nearly totally misclassified as bare soil (it looks like bare soil on the photography), not-classified areas correspond to dark bare soil areas within the field. In another field, the 60 m data show not-classified points at the

edge between a bare soil section and a section where there appears to be straw on the ground. The mixture appears dissimilar to either bare soil or stubble. In a third field, the area is so mottled that at 60 m, sizable averaging of green vegetation, stubble, and dark bare soil occurs. The field is quite small (only 3 pixels at 60 m) and the results of the averaging are data points which do not resemble any signature enough to be recognized.

Ripe Oats

Since ripe oats were perfectly recognized at all spatial resolutions, no further discussion of accuracy will be made.

Pasture

The pasture class is spectrally quite variable, ranging from lush green pastures to nearly bare soil. The training set was selected from pastures of intermediate, but uniform, grass cover, as judged from the CIR photography.

The major effects on pasture recognition when going from 15 to 60 m data are the decrease in stubble misclassification, the increase at 30 m and then decrease of woods misclassification, and the increase in the not-recognized case at both 30 and 60 m. Summaries of results for individual fields are presented in following paragraphs, with detailed discussion in Section B.3.

Substantial stubble recognition occurs in four fields. In one, the field is so sparse that it is completely classified as stubble at each resolution. Two fields have stubble recognition in sparse covered areas which are small and distributed through the field. Averaging of pixels lumps data from these sparse areas along with normal points, and the resultant data are called (incorrectly) sparse corn. At 60 m, the field is only 2 pixels wide and 4 pixels long, and at this resolution the averaging is so severe that all pixels are

incorrectly called sparse corn. A fourth field shows stubble recognition in areas of sparse vegetation cover adjacent to dark bare soil. As the pixels are averaged with the dark-bare-soil pixels, the points are not classified (at the coarser resolutions).

Woods recognition is primarily in two pasture areas, one where there is substantial brush in one corner, and the other with one or two trees. Woods recognition decreases in the pasture with one or two trees as resolution element size increases. This occurs because of the averaging of the tree pixels with the surrounding pasture pixels. In the other pasture, the tree recognition stays about the same as pixel size is increased because the area of brush is relatively large.

The not-recognized category increases in size as we move from 15 to 60 m resolution. This increase can be explained by the averaging of dark soil pixels with normal pasture pixels at the coarser resolutions. Resultant composite pixels are not classified, thus increasing the size of the not classified class.

Dense Green

The major effect on dense green recognition when going from 15 to 60 m is a reduction in the amount of woods misclassification. Trees are generally scattered throughout some of the dense green fields just as they were through pastures. Since the woods are scattered, averaging with valid dense green points produces data which are called dense green.

Woods

The only significant effect of increasing the resolution element size on woods recognition is a slight reduction in the corn misclassification. As previously noted, corn recognition occurs in small areas of sparse woods. Again, the averaging of these small areas with more-homogeneous areas of woods at the larger resolution element sizes results in pixels classes as woods.

B.3 ANALYSIS OF PASTURE RECOGNITION

Because the test set evaluation of pasture yielded very low accuracy results at all spatial resolutions, and because our analysis of test set data with CIR photography revealed that pastures are a spectrally variable class, we decided to do a more thorough analysis of the recognition patterns in pasture areas.

The August data set registered pasture areas at very nearly their most variable stage. Some pastures had not been grazed and had developed lush dense green canopies. Other areas had been grazed and showed a typically mottled pattern varying from gray or blue (bare soil) to pink (dense vegetation) on the CIR film. The variation within pasture areas was in some cases as great as the variation between bare soil and dense green vegetation.

In a mission sense, a better time to collect data for pasture recognition would be in spring, right after fields had been plowed, or possibly early spring when pastures are green (along with winter wheat), and cattle have not been allowed to graze on the forage. At those times, pastures as a class would be spectrally more homogeneous, and easier to separate from other scene materials.

We performed two analyses on the pasture test set data, the first a quantitative comparison involving the test set classification results where the results were compared to a trained, unbiased photointerpreter's estimate of the composition of each test field. Results are discussed in a section below. Second, for one pasture test set, we quantitatively estimated the percentage composition by a dot-grid technique applied to the photography. The quantitative estimate was then compared with the recognition estimate.

In deriving the photointerpreted results, the distinction between density classes of vegetation (represented by the classifier classes dense green, sparse corn, pasture, stubble, and bare soil, progressing from dense to sparse vegetation cover) was subjectively estimated.

Discrepancies of ± one density class are to be expected between photointerpreted results and classifier results. For example, the photointerpreter might have called a particular area sparse corn while the processor called the area pasture or perhaps dense green.

A total of eight pasture test sets were examined. These are discussed individually in following paragraphs. Definitions are given in Table B-5.

Field 61 (Table B-5)

Field 61 is a pasture in the southern end of the flight line. The photointerpretation and recognition results are summarized in Table B-5. It is a fairly typical pasture with sparse grass cover in the middle and lush grass along the southeastern and western field borders. Some dead grass spots are noticeable in the center.

Field 62 (Table B-6)

This pasture is a fairly lush pasture with some sparse areas apparent in the center. Isolated small bare spots are also visible. Table B-6 summarizes the accuracy of the classification and compares the recognition output with the photointerpreted results.

Field 63 (Table B-7)

This relatively lush pasture is very similar in appearance to Field 62. Vegetation percentage cover differences are apparent on the photography, with areas in the north center of the field having lower cover than other areas. Table B-7 compares recognition and photointerpretation results.

Field 65 (Table B-8)

This field is a very lush pasture which has not been grazed for some time, although animal trails and bare spots where a watering

TABLE B-5. FIELD 61 RECOGNITION AND PI DATA
96-15m Pixels in the Field Test Set

	PERCENTAGE COMPOSITION	
CLASS	RECOGNITION	PHOTO-INTERPRETATION
Woods	8.3	1
Pasture	80.1	69
Ripe Oats	4.2	20
Sparse Corn	7.4	10

Weighting Factor* = .1111
Accuracy** = 72.46%

*Weighting factor is the fraction of the total test set size present in this field.

**Defined as: $100-[\Sigma(\%rec - \%PI)^2]^{1/2}$, where rec is computer recognition and PI is photo-interpretation

TABLE B-6. FIELD 62 RECOGNITION AND PI DATA
96-15m Pixels in the Field Test Set

	PERCENTAGE COMPOSITION	
CLASS	RECOGNITION	PHOTO-INTERPRETATION
Dense Green	67	50
Sparse Corn	33	40
Woods	0	10

Weighting Factor = 0.1111 Accuracy = 79.07%

C-4

TABLE B-7. FIELD 63 RECOGNITION AND PI DATA
16-15m Pixels in the Field Test Set

CLASS	RECOGNITION	PHOTO-INTERPRETATION
	PERCENTAGE COMPOSITION	
Sparse Corn	18.8	30.0
Stubble	43.7	50.0
Pasture	0	20.0
Dense Green	37.5	0

Weighting Factor = 0.0185
Accuracy = 55.73%

TABLE B-8. FIELD 65 RECOGNITION AND PI DATA
128-15m Pixels in Field Test Set

CLASS	RECOGNITION	PHOTO-INTERPRETATION
	PERCENTAGE COMPOSITION	
Dense Green	0	20
Sparse Corn	86	80
Stubble	14	0

Weighting Factor = 0.1481
Accuracy = 74.86%

trough or food bins have been are apparent. It was recognized primarily as sparse corn because of the relatively lush vegetation growth.

Field 66 (Table B-9)

This pasture, near the I-96 freeway, is very sparsely covered with grass and has considerable bare soil showing. The field was 100 percent recognized as stubble. This is caused by the presence of some apparently dead vegetation (yellow tones on the CIR film).

Field 67 (Table B-10)

This pasture, just north of the I-96 freeway, has lush vegetation spots, along with areas of dark bare soil and considerable brush growing in the southwest corner of the test set. The lush spots are recognized as dense green, while the brush areas are recognized as trees. Pasture and sparse corn split the remainder of the test set, with areas of sparser grass cover being recognized as pasture.

Field 68 (Table B-11)

This pasture is quite variable, with lush vegetation apparent in the northwest corner and in two north-south strips in the field center. The remainder of the area is quite sparse grass cover with considerable bare soil apparent. Some strictly bare soil spots are visible. Table B-11 summarizes recognition and photointerpretation results.

Field 60 (Table B-12)

This field has relatively dense vegetation cover, but is mottled, indicating some variation of cover over the field. Some areas of dark bare soil or possibly stubble are apparent in the south central part of the field. Table B-12 summarizes the recognition and photointerpretation results.

TABLE B-9. FIELD 66 RECOGNITION AND PI DATA
64-15m Pixels in Field Test Set

	PERCENTAGE COMPOSITION	
CLASS	RECOGNITION	PHOTO-INTERPRETATION
Dense Green		20
Stubble	100.0	80

Weighting Factor = 0.0741

Accuracy = 71.72%

TABLE B-10. FIELD 67 RECOGNITION AND PI DATA
144-15m Pixels in Field Test Set

	PERCENTAGE COMPOSITION	
CLASS	RECOGNITION	PHOTO-INTERPRETATION
Woods	55.5	25.0
Sparse Corn	1.4	30.0
Dense Green	19.4	20.0
Pasture	22.9	25.0

Weighting Factor = 0.1667

Accuracy = 58.13%

TABLE B-11. FIELD 68 RECOGNITION AND PI DATA
256-15m Pixels in Field Test Set

CLASS	PERCENTAGE COMPOSITION RECOGNITION	PHOTO-INTERPRETATION
Stubble	31.5	48.0
Sparse Corn	1.0	10.0
Bare Soil	0	2.0
Pasture	63.7	40.0
Not Classified	3.1	0

Weighting Factor = 0.2963
Accuracy = 69.53%

TABLE B-12. FIELD 60 RECOGNITION AND PI DATA
64-15m Pixels in Field Test Set

CLASS	PERCENTAGE COMPOSITION RECOGNITION	PHOTO-INTERPRETATION
Bare Soil	0	10.0
Stubble	32.9	25.0
Dense Green	51.6	45.0
Sparse Green	0	20.0
Dense Corn	1.6	0
Not Classified	14.0	0

Weighting Factor = 0.0741
Accuracy = 73.45%

Detailed Analysis of Field 67 (Table B-13)

To more quantitatively explore the correlation between the photointerpreted estimates of field content and recognition results, additional analysis was performed on Field 67. Photointerpretation quantitatively estimated the percentage of each category within the test set boundaries in Field 67 using a dot-grid technique. The results were then compared to the recognition results as shown in Table B-13.

The average accuracy, using this comparison method was 36.1 percent compared with 58.1 percent for the accuracy using the qualitative field composition analysis. The major discrepancy in both the results occurs in the recognition of the brush category. Recognition processing overestimates this category within this particular field, and this accounts for the reduced field recognition accuracy. In general, it is not likely that brush of this density will occur in pastures, so the condition in this test set is somewhat abnormal for pastures in general.

B.4 EFFECTS OF COST FACTORS ON CLASSIFIER PERFORMANCE ON PASTURES

In an effort to improve the correct classification of pastures by reducing false alarms from sparse corn, dense green, and ripe oats, cost factors were introduced in the decision rule to selectively penalize various misclassifications, e.g., pasture misclassified as sparse corn was penalized more heavily than sparse corn misclassified as pasture. Originally, equal weights (costs) were used.

Using cost factors as shown in Table B-14, the test set was reclassified using the same signatures and channels as the original case. The 15 m data were used for this test.

Results of the classification, for pastures, are shown in Table B-15, along with the results from the equal-cost case previously run. There was modest improvement in the pasture recognition accuracy

TABLE B-13. QUANTITATIVE RECOGNITION AND PI COMPARISON FOR FIELD 67
144-15m Pixels in Field Test Set

	PERCENTAGE COMPOSITION	
CLASS	RECOGNITION	PHOTO-INTERPRETATION
Woods	55.5	9.6
Sparse Corn	1.8	35.8
Dense Green	19.8	1.3
Pasture	22.9	35.4
Stubble	0	17.9

Average Accuracy = 36.1%

TABLE B-14. COST FACTORS FOR REVISED RECOGNITION OF PASTURES

	Classifier Class								
	BS	DS	SC	SOY	ST	RO	P	DG	W
Bare Soil	X	1	1	1	1	1	1	1	1
Dense Corn	1	X	1	1	1	1	1	1	1
Sparse Corn	1	1	X	1	1	1	1	1	1
Soybeans	1	1	2	X	1	1	1	2	1
Stubble	1	1	1	1	X	1	1	1	1
Ripe Oats	1	1	1	1	1	X	1	1	1
Pasture	1	1	2	1	2	2	X	2	1
Dense Green	1	1	2	1	1	1	1	X	2
Woods	1	1	1	1	1	1	1	1	X

e.g.: The cost of calling pasture sparse corn is 2.

The cost of calling sparse corn pasture is 1.

TABLE B-15. EFFECTS OF COST FACTORS ON RECOGNITION OF PASTURES % CLASSIFICATION
(FIRST # SHOWS RESULTS WITH ORIGINAL DECISION RULES)

FIELD NUMBER	BARE SOIL	DENSE CORN	SPARSE CORN	SOY	STUBBLE	RIPE OATS	PASTURE	DENSE GREEN	WOODS	NOT CLAS.
60		1.6			32.8			51.6		14.1
(64)		1.6			29.7			53.1		15.6
68			1.2		31.6		63.7	.4		3.1
(256)					28.1		68.8			3.1
67			1.4			.7	22.9	19.4	55.6	
(144)			1.4			.7	25.0	19.4	53.5	
66					100.0					
(64)					100.0					
65			85.9		14.1					
(128)			83.6		16.4					
63			18.8		43.8			37.5		
(16)			18.8		43.8			37.5		
62			32.3					67.7		
(96)			25.0					75.0		
61			7.3			4.2	80.2		8.3	
(96)			4.2			5.2	82.3		8.3	

PCT CORRECT CLASSIFICATION = 31.6 (ORIGINAL RULE
33.67 (WEIGHTED RULE)

*No. pixels in field

overall, but the classification of some pastures did not change (e.g., 63 and 66). The change in the classification of other areas was more modest.

The reasons why the classification did not change more dramatically are probably because of the extreme spectral variability in pastures and because the cost factors were not enough different from unity to cause major changes in recognition boundaries.

When photointerpreted results are taken to be the true composition of the eight pastures, the computer recognition accuracy becomes 70 percent, compared with 31.6 percent if all points in pasture were actually pasture.

The use of cost factors to bias the recognition results to permit more pasture recognition in pastures and fewer false alarms of sparse corn, dense green and oats improved recognition in pastures slightly from 31.6 percent to 33.7 percent. Apparently, more drastic cost factors than the 2:1 factors used are required to materially alter the processing results on this data set.

APPENDIX C

PROCESSING AND ANALYSIS OF S192 DATA

PROCESSING AND ANALYSIS OF S192 DATA

C.1 INTRODUCTION

At the outset of the study, it was felt that processed S192 data would provide a valuable baseline on the performance of pattern recognition devices on multispectral, broad spectral coverage (0.4-12.5 μm) spacecraft data. Accordingly, test sites were selected where S192 data and supporting aircraft under-flight data were available. Previous sections of the report have dealt with the analysis and processing of the aircraft scanner data. This section details the processing and analysis of the S192 data.

Although S192 data were ordered from five test sites, data from only four were processed and analyzed. The fifth data set, from North Dakota was retained as a backup. Processing of White Sands and Atchafalaya data were completed at ERIM and Baltimore data were processed at Honeywell-Minneapolis. Processing the Michigan data was started at ERIM, but was not completed by the end of the contract because of technical difficulties.

Because the S192 data were noisy when originally collected (the sensor was not operating in normal fashion), noise reduction techniques were designed to preprocess the data before analysis could begin. These noise reduction techniques, developed in February 1974 before the production processing system was fully operational, were successful in reducing the noise on the data, but noise was not entirely eliminated. The resultant data were thus noisy enough to represent the upper limit of NE$\Delta\rho$ for most applications we examined. Accordingly, the aircraft data simulated cases of higher radiometric fidelity than the S192 sensor. Because of the radiometric quality of the S192 data, the planned radiometric studies were not performed. Studies were performed on the rank ordering of S192 spectral channels for various applications and the classification accuracy obtainable

with different numbers of bands. These study results are reported in this appendix.

C.2. APPROACH

As previously mentioned, noise reduction algorithms were designed and implemented before the actual processing of the data commenced. In this section, both the noise reduction and the processing approaches will be discussed.

C.2.1 NOISE REDUCTION

The S192 data, as recorded on the spacecraft, were more noisy than expected, as a result of non-optimum sensor operation. Three types of noise appeared at unexpected levels in the data — 1/f or low frequency noise with a period of several scan lines, herringbone medium frequency noise caused by mechanical cooler piston action, and high frequency white noise. These types of noise had been recognized early in the analysis of data, and ERIM were already under contract to assist JSC personnel in defining the filtering schemes and filter parameters to reduce noise to acceptable levels.

As a first step in the processing, power spectra analyses were performed on the data from each of the five areas to determine the dominant frequencies of the noise sources and the amplitude of each source. Then filtering schemes and coefficients were designed.

The reduction of 1/f noise was handled differently from the reduction of herringbone noise. Because the 1/f noise had a frequency of only fractions of a cycle per scan, the dark level clamping algorithm already planned for use as part of the calibration system package would be effective in reducing this noise level. The noise appeared as a "bounce" on the signal, and to a first approximation, each point of a given scan line was offset from the corresponding point on the previous line by a constant amount. The amount of this offset varied

from line to line. Because an offset was involved, the clamping system should have removed all of the variation. However, it was difficult to obtain an accurate estimate of the dark level (or cold reference plate for the thermal channel) because some of the data values exceeded the dynamic range of the A/D converter on board the spacecraft. Accordingly, a revised dark level was estimated by fitting a Gaussian curve to the valid data points, then estimating a new mean value for the dark reference. This new mean value was used as the dark reference. Clamping all data values to this revised dark reference effectively reduced the 1/f noise because a new dark reference was calculated by each scan line. The noise varied for signal level at rates considerably less than the scan line rate.

A different filtering approach was used to remove the herringbone noise. Because the noise consisted of a set of well defined frequencies in the video bandwidth, sharp notch filters were designed to remove the energy at the frequencies of the noise. Because sharp notch filters transient response includes ringing, and the ringing is more severe for narrower filter notches (for a given notch shape), the best filter for removing the herringbone noise while retaining as much of the original video data unaltered was a compromise. The suitable filters were implemented as digital filters, using a program developed by the Jet Propulsion Laboratory (JPL).

Both the clamping and the digital filtering of data were performed by NASA at JSC. Data calibration and scan line straightening, to produce standard product S053, completed the preprocessing of the S192 data.

C.2.2 PROCESSING TECHNIQUES

Processing techniques used for the S192 data were very similar to those used for the aircraft data as discussed in Section 2. However, the approach will be further discussed here.

C.2.2.1 WHITE SANDS GEOLOGY DATA PROCESSING

The White Sands data for the Geology case were collected on the SL-2 mission on 14 June 1973, and pertinent characteristics of the data are summarized in Table C-1.

The first step in processing was to copy the 9 track 800 bpi data sets to the 7 track 800 bpi ERIM standard format for further processing. This step was accomplished on an IBM 360 computer. Special software was developed for this task, with support for the development coming partly from this contract and partly from other Skylab investigations at ERIM.

The next processing step (see Figure C-1) was to prepare a graymap of the red band for location of training sets and verification of data coverage and quality. Using ground information gathered from geologic maps and past geologic studies, training sets for important rock and soil types in the White Sands Area were located on the graymap.

Before signatures were extracted for the geologic materials, a set of promising ratio features were defined by analysis of Earth Resources Spectral Information System (ERSIS) data of the materials likely to be found in the scene. ERSIS library spectra were then edited, using standard programs, to yield spectra of materials likely to be in the scene. A set of likely materials was then determined from analysis of ground truth information. Of 98 possible ratios, twenty promising ratios were defined by calculating reflectance ratio data from ERSIS (band averaged over S192 spectral bandwidths), and selecting ratios which separated the scene materials.

When the twenty-four promising ratios were identified, signatures from the training sets, previously located on the graymap, were extracted. A transformation routine was then used to calculate ratio feature signatures directly. Before forming the ratio features for signature calculation, the darkest object level was subtracted from each signal value in the channels to be divided.

TABLE C-1. DATA CHARACTERISTICS
White Sands S-192 Data

SPECTRAL CHANNELS AVAILABLE

.41 - .46 μm	.78 - .88	10.2 - 12.5
.46 - .51	.98 - 1.03	
.52 - .56	1.09 - 1.19	
.56 - .61	1.20 - 1.30	
.62 - .67	1.55 - 1.75	
.68 - .76	2.10 - 2.35	

SPATIAL RESOLUTION CASES CONSIDERED

80 m

OTHER PERTINENT DATA

Date of Collection:	14 June 1973
Flight Altitude:	260 n. mi.
Sensor:	S-192, S-190A SL-2 Mission
Time of Day:	1444:42.3 - 1445:00.0 GMT
Quantity of Data:	40 x 100 n. mi.

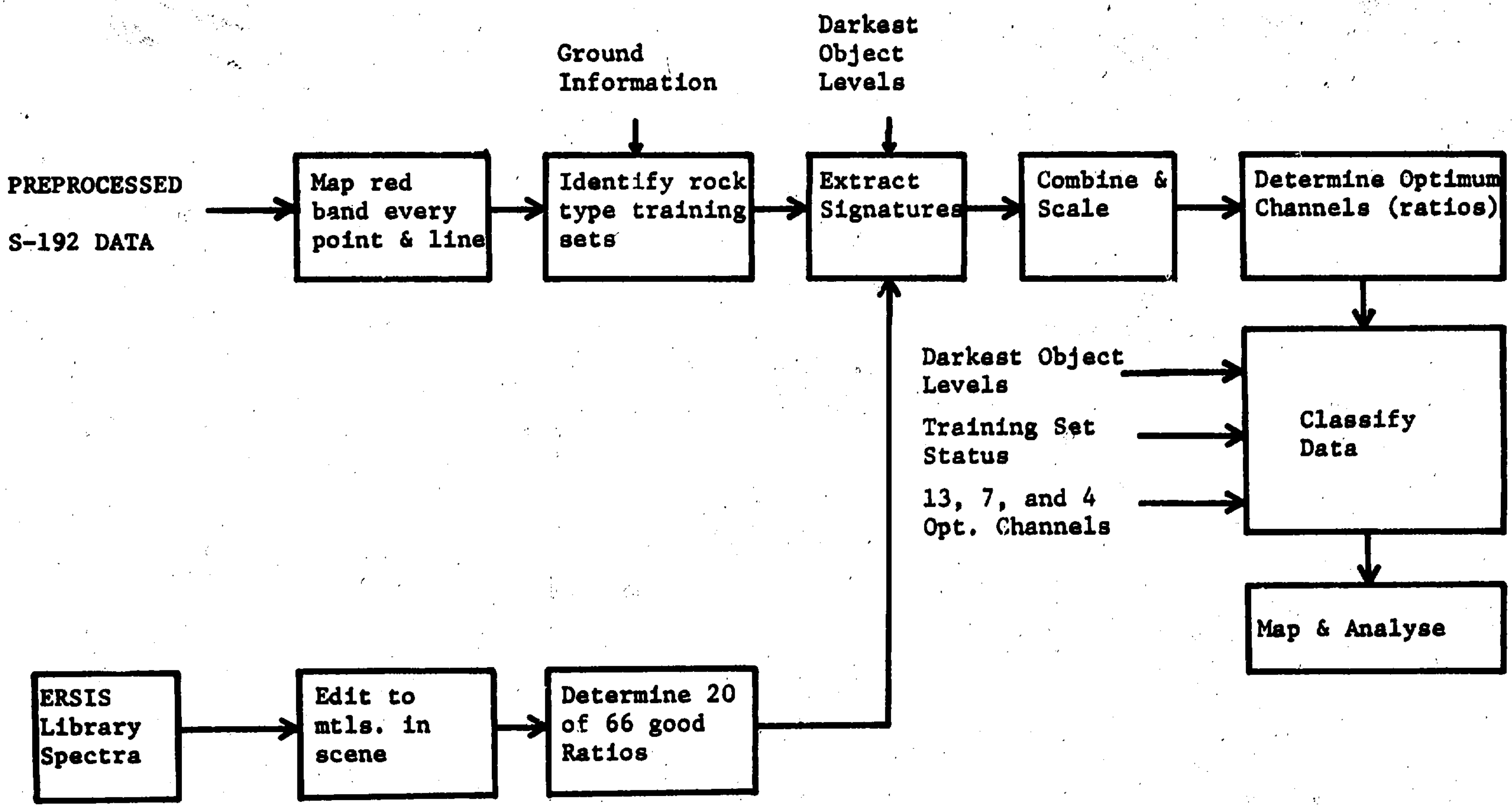

FIGURE C-1. FLOW OF S-192 PROCESSING OPERATIONS FOR GEOLOGY DATA

Signatures extracted from the training sets were then analyzed for consistency, and signatures of like materials combined to form training set statistics more characteristic of the class to be recognized. The optimum ratio features, and the spectral channels comprising these ratios were prioritized by the feature selection program.

Data were then classified, using the composite training set statistics, the optimum 13, 7, or 4 channels and the darkest object levels previously determined in preprocessing. Recognition maps were displayed and analyzed to determine the correct and incorrect classification of geologic materials.

C.2.2.2 BALTIMORE LAND USE DATA PROCESSING

The S192 data for the Baltimore Land Use Test Site were collected on the SL-3 mission on 5 August 1973, and pertinent characteristics of this data set are shown in Table C-2. All processing of the Baltimore S192 data was done at Honeywell-Minneapolis.

After format conversion, all bands of the S192 data were converted to imagery on the Optronics filmwriter. Also digital computer graymaps of the red band were made to allow selection of training sets and to locate the area covered by the S192 data (see Figure C-2).

Before continuing with the processing, Anderson Level II ground information provided by R. Alexander of USGS was digitized and merged with the S192 data to provide a base for selection of training sets and for evaluating the ultimate map product. Then training sets for Anderson Level II categories were extracted from three sub-areas of the total S192 data — Washington, D. C., Baltimore, and an area halfway between Washington and Baltimore.

After training sets had been selected, and the various samples of each Level II land use class combined to create composite signatures, the ordering of spectral channels was performed using the mapping error criterion.

TABLE C-2. DATA CHARACTERISTICS

Baltimore S-192 Data

SPECTRAL CHANNELS AVAILABLE

.41 - .46 μm	.78 - .88	10.2 - 12.5
.46 - .51	.98 - 1.03	
.52 - .56	1.09 - 1.19	
.56 - .61	1.20 - 1.30	
.62 - .67	1.55 - 1.75	
.68 - .76	2.10 - 2.35	

SPATIAL RESOLUTION CASES CONSIDERED

80 m

OTHER PERTINENT DATA

Date of Collection:	5 August 1973
Flight Altitude:	235 n. mi.
Sensor:	S-192, S-190B, S-190A, SL-3 Mission
Time of Day:	1503: 48.6 - 1504: 01.3 GMT
Quantity of Data:	40 x 61 n. mi.

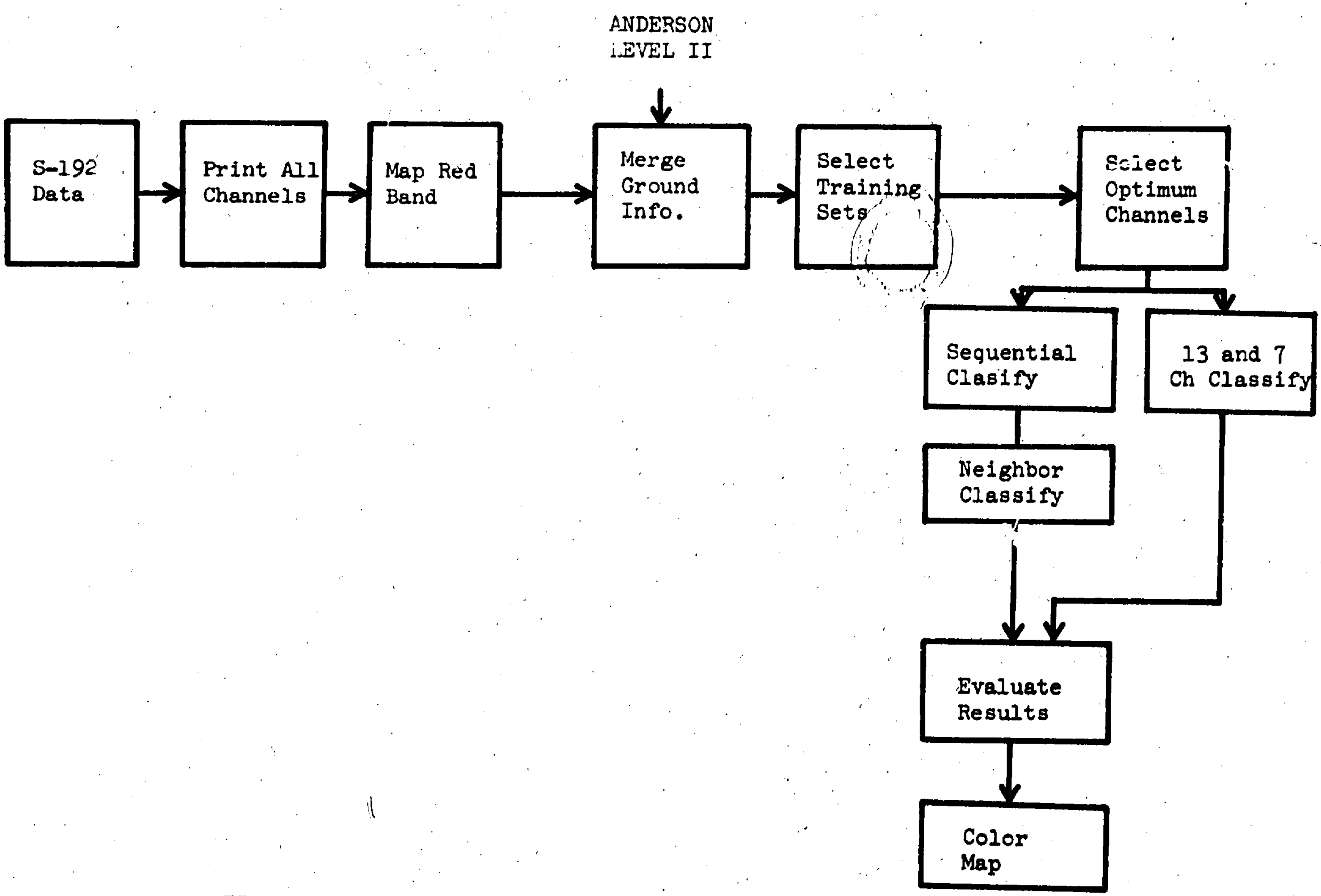

FIGURE C-2. S-192 BALTIMORE DATA PROCESSING FLOW

Classification was performed using the K-class classifier and various approaches. The first approach was a conventional one-pass classification approach using the best seven and all thirteen spectral bands. In another approach, sequential classification was attempted, using a few channels to distinguish broad land use classes, then using other channels and the broad class assignment to perform more detailed recognition. Finally, an approach combining the sequential classification with a modification of the decision rule which adjusted the recognition of a pixel to conform to the identification of its neighbors, was implemented. The details of this procedure are discussed in Section C.3.2 of this appendix.

The classification results were evaluated using a test set of points. A color coded recognition map of the data was also prepared.

C.2.2.3 ATCHAFALAYA WATER QUALITY DATA PROCESSING

The Atchafalaya data for the water quality study was collected on the SL-3 mission on September 19, 1973, and pertinent characteristics of this data set are summarized in Table C-3.

After format conversion, both red and near infrared (0.78-0.88 μm) bands were mapped to provide a picture of the terrain. Both bands were mapped to provide a picture of the vegetation classes (portrayed by the red band) and the vegetation — water interface (portrayed by the near infrared band).

Because of the priority of the water quality study, relative to the mapping of the agriculture classes (nearly all of the agriculture was sugar cane) and the natural vegetation (a great deal of which was cypress-tupelo forest), this investigation was pursued, as shown in Figure C-3.

Initially, the data were edited to cover the same general area as the MSDS data previously discussed, but there was incomplete overlap of the aircraft coverage and the S192 coverage. After editing,

TABLE C-3. DATA CHARACTERISTICS

Atchafalaya S-192 Data

SPECTRAL CHANNELS AVAILABLE

.41 - .46 μm	.78 - .88	10.2 - 12.5
.46 - .51	.98 - 1.03	
.52 - .56	1.09 - 1.19	
.56 - .61	1.20 - 1.30	
.62 - .67	1.55 - 1.75	
.68 - .76	2.10 - 2.35	

SPATIAL RESOLUTION CASES CONSIDERED

80m

OTHER PERTINENT DATA

Date of Collection:	19 September 1973
Flight Altitude:	260 n. mi.
Sensor:	S-192, S-190B, S-190A
Time of Day:	1345:57.8 - 1346:16.8 GMT
Quantity of Data:	40 x 76 n. mi.

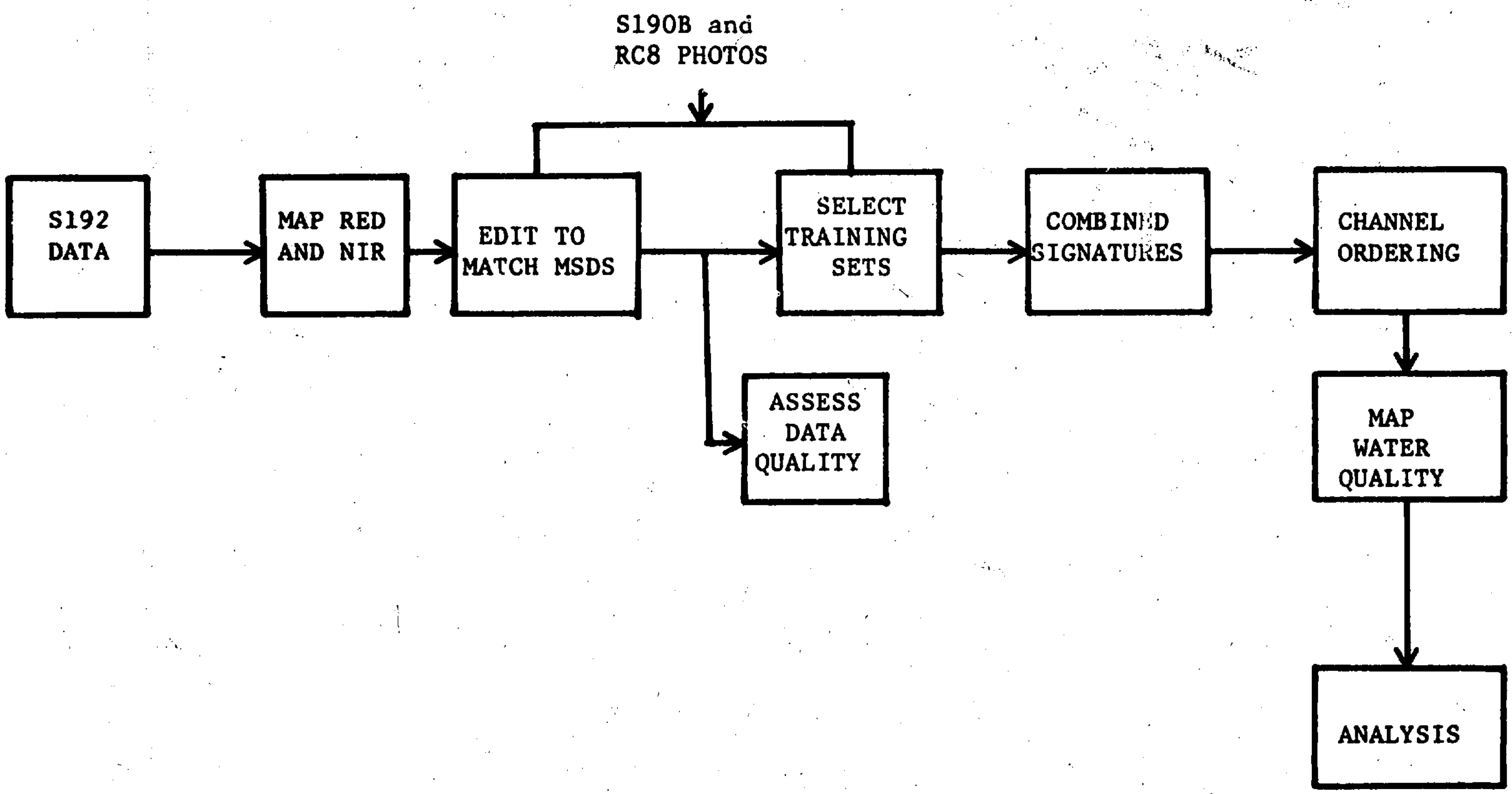

FIGURE C-3. S-192 ATCHAFALAYA DATA ANALYSIS

water of various turbidity classes were identified on S190A and RC-8 photography and located on graymaps of the area.

At the same time as signatures were being located and extracted, an analysis of data quality was made to determine the level of noise, and to obtain some estimate of the number of classes of water quality which could be discriminated.

Signatures for various water quality types were combined to yield a set of composite signatures for water quality mapping and determination of optimum channels for mapping. Then the optimum channels were determined.

A map of water quality was made using the S192 data. Prior to mapping various water quality types, the water data was separated from the land data by slicing the 0.78-0.88 μm band. The map was later analyzed as reported in Section 3.3 of this report.

C.2.2.4 MICHIGAN AGRICULTURE DATA PROCESSING

Although the intent was to process the S192 data collected over the Michigan Agriculture test site on 5 August 1973, to obtain a recognition map of crops, this effort was not completed by the end of the contract. The major problem encountered with this data set was the difficulty in locating training sets for the major crops. Two factors are felt to be responsible for this difficulty. First, the data were collected on a very hazy day, and the contrast of the scene was reduced as a result. Second, the field patterns in the Michigan data are relatively small, with many fields less than 20 acres and nearly all fields less than 80 acres. Under these conditions with ERTS data, training fields of 40 acres or less have proven difficult to find.

Procedures were initiated to locate training sets by locating the sets on a topographic map and photography, then translating the location to the S192 data through the use of control points visible

on both S192 and photography or map data. We were unable to complete this work before the end of the contract, and it is being continued under our Skylab investigations.

C.3 PROCESSING RESULTS

As a result of the processing procedures detailed in Section 2, processed products were obtained for the Baltimore, White Sands, and Atchafalaya sites. In this section, the intermediate and final results of the processing are presented and discussed.

C.3.1 WHITE SANDS DATA RESULTS

After preparing a red band graymap, and consulting existing geologic maps and other information, a number of training sets were selected from the data. After considerable analysis of the signatures, the thirty signatures shown in Table C-4 were defined for classifying the data. The signatures are divided into five main groups roughly organized according to composition — ferric iron containing materials, calcareous materials, igneous rocks, clays, and other materials.

In parallel with the effort to locate training sets, we instituted an investigation to define promising ratio features from S192 data using the spectral reflectance information from the ERSIS Library. Analysis defined the twenty-four ratio features shown in Table C-5 as ones which well separated the thirty signatures. Next, the ordering of the features was accomplished by a digital computer program STEPL [26]. The results of the analysis are shown in Table C-6. Shown in Table C-6 along with the ratios, in order of selection, is the average pairwise probability of misclassification for the thirty training sets.

TABLE C-4. S-192 WHITE SANDS DATA
TRAINING SETS

<u>Ferric Iron Containing Materials</u>

Red soil and sediment
Recently deposited red soils
Red soil
Red sandstone? (Sacramento Mountains)
Red sandstone? (Sacramento Mountains) - 2nd sample
Brown soil
Red soil - 2nd sample
Red soil - 3rd sample
Iron stained sandstone - Yeso - San Andres Formation

<u>Precambrian Igneous Materials</u>

Precambrian crystalline granite and schist

<u>Calcareous Materials</u>

Dolomite and dolomitic sandstone
Calcareous shales and argillaceous limestones
Argillaceous limestones and calcareous dastics - Hueco formation
Dark colored limestone
Sediment - Jarilla Mountains

<u>Clay Materials</u>

Dark drainage deposits } Dark Bolson Sediment
Dark colored sediment
Dark pediment } Bolson Sediment
Valley sediment
Reminant rock

<u>Other</u>

Gypsum sands
Multicolored sediment
Light colored pediment
Gray soil
Crystalline rock - Jarilla Mountains
Pediment
Pediment - 2nd sample
Valley fill
Valley sediment

TABLE C-5. RATIOS SELECTED FROM ERSIS FOR S-192
White Sands Geology Data

2.10-2.34/1.03-1.19	0.93-1.05/0.77-0.89
2.10-2.34/0.77-0.89	0.93-1.05/0.60-0.65
2.10-2.34/0.60-0.65	0.93-1.05/0.50-0.55
1.55-1.73/1.15-1.28	0.77-0.89/0.65-0.73
1.55-1.73/0.93-1.05	0.77-0.89/0.50-0.53
1.15-1.28/1.03-1.19	0.65-0.73/0.50-0.53
1.15-1.28/0.93-1.05	0.65-0.73/0.45-0.50
1.15-1.28/0.65-0.73	0.60-0.65/0.50-0.53
1.15-1.28/0.50-0.55	0.60-0.65/0.45-0.50
1.03-1.19/0.93-1.05	0.60-0.65/0.42-0.45
1.03-1.19/0.65-0.73	0.50-0.55/0.42-0.45
1.03-1.19/0.50-0.55	0.45-0.50/0.42-0.45

TABLE C-6. THIRTEEN OPTIMUM RATIOS, IN ORDER OF PRIORITY, FOR S-192 WHITE SANDS DATA

Ratio	Average Pairwise Prob. of Misclass.
2.10-2.34/0.77-0.89	0.274
1.03-1.19/0.50-0.55	0.184
0.65-0.73/0.50-0.55	0.151
0.45-0.50/0.42-0.45	0.132
0.65-0.73/0.45-0.50	0.119
1.03-1.19/0.93-1.05	0.109
1.55-1.73/0.93-1.05	0.098
2.10-2.34/0.60-0.65	0.091
0.93-1.05/0.77-0.89	0.086
0.77-0.89/0.50-0.55	0.083
0.60-0.65/0.50-0.55	0.081
1.15-1.28/0.50-0.55	0.080
2.10-2.34/1.03-1.19	0.078

C.3.1.1 CHANNEL ORDERING RESULTS

There is physical significance to the band ratios selected. The first ratio (2.10-2.34 μm/0.77-0.89 μm) is the ratio of two bands which separate the carbonates from those classes containing ferric iron. In 0.77-0.89 μm, the ferric iron containing materials have lower reflectance than at 2.1-2.35 μm because of the absorption by the ferric ion in 0.77-0.89 μm. Conversely, the carbonates have higher reflectance in 0.77-0.89 μm than at 2.1-2.35 μm because of absorption of the carbonate ion at the longer wavelengths. Thus, the ratio value for carbonates will be high and low for ferric iron containing materials.

With the second ratio (1.03-1.19 μm/0.50-0.55 μm), ferrous iron containing materials are separated from those containing ferric iron. In the 1.03-1.19 μm region the reflectance of ferrous iron compounds is low because of absorption by that ion. Ferric compounds show intermediate reflectivity. At 0.50-0.55 μm the reflectance of ferrous iron compounds is relatively high, while the reflectance of ferric iron compounds is low because of absorption by that ion. Consequently this second ratio will have low values for ferrous iron and high values for ferric iron containing materials.

The third ratio separates the ferric iron containing materials from all others in the scene. As a result of ferric iron absorption, the reflectance of ferric iron containing materials is very low in the green region (0.50-0.55 μm). In the far red region, there is no absorption by this ion. Consequently the red/green ratio 0.67-0.73 μm/0.50-0.55 μm has large values for ferric iron containing materials and intermediate or low values for other materials.

The fourth ratio separates the hydroxyl ion containing materials (primarily clays) and the ferrous iron containing materials from the carbonates and light felsitic igneous rocks. The reflectance of the former materials drops in the region covered by the two bands, while the ratio for the latter materials will be low.

Beyond these four ratios, there are few of obvious physical significance. Ratio 11 (0.60-0.65 μm/0.50-0.55 μm) is a ratio similar to ratio 3 (0.65-0.73 μm/0.50-0.55 μm) with the red band placed partially in the ferric iron absorption band. Band ratios having the 2.1-2.35 μm channel in the numerator probably are effective in delineating carbonates and clays from the other materials because of hydroxyl and carbonate ion absorption in that band.

C.3.1.2 RECOGNITION RESULTS

Recognition maps of a portion of the White Sands Test Site were prepared using the best three, four and eleven ratios, corresponding to 5, 7, and 13 channels respectively. The area processed, Figure C-4, was one with relatively good ground information and one containing a majority of the training sets. The area shown is 47 km x 37 km in dimension, located near the gypsum dunes of the White Sands National Monument. The eleven ratio recognition map and associated color code are shown in Figure C-5. Recognition accuracy chekcs were carried out for training sets only since limited ground truth data and low altitude aerial photography precluded identification of suitable test sets.

The data was analyzed two ways. First, the accuracy of delineating four of the five basic compositional types of materials in the scene was assessed. Accuracy was then assessed for a six class map where each compositional type had one or more subclasses. Satisfactory classification accuracy was not obtained on all the thirty signatures that we chose for the recognition, so the recognition of some of these signatures were combined.

C.3.1.2.1 Three Ratio Results

Tables C-7, C-8, and C-9 show the classification accuracy results for both four and six class cases with three, four, and

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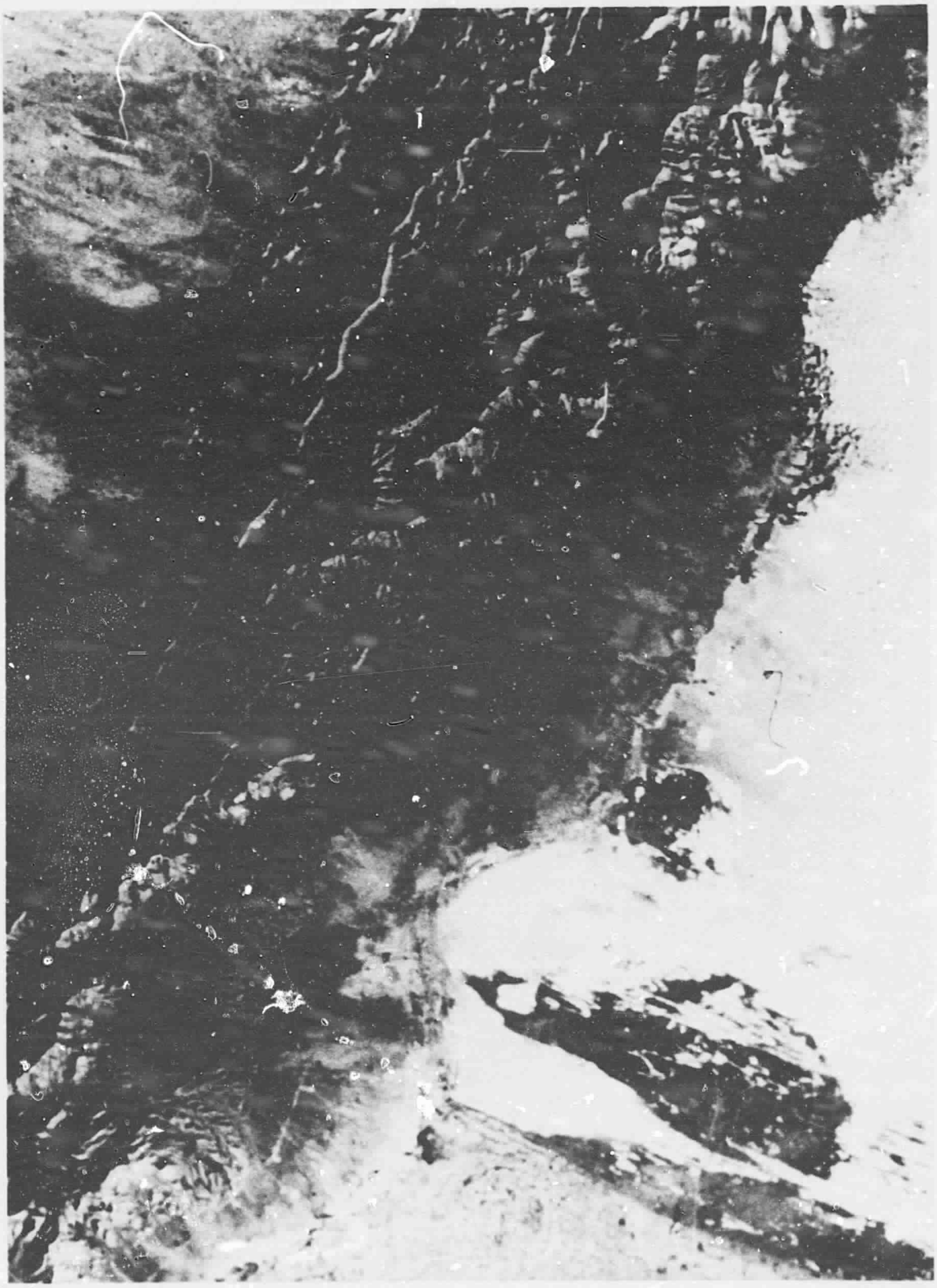

FIGURE C-4. S-190A COLOR PHOTOGRAPH OF WHITE SANDS TEST SITE

FIGURE C-5. S-192 ELEVEN RATIO COLOR-CODED RECOGNITION MAP
OF WHITE SANDS TEST SITE

COLOR	CLASS
Light Blue	Gypsum sand
Medium Blue	Bolson sediment
Dark Blue	Terrain Shadow
Green	Alluvium
Dark Green	Dark Bolson sediment
Pink	Red Alkali Soil
Red	Red Alkali Deposits
Dark Red	Gypsiferous Soils
Gray	Soils
Black	Precambrian rocks

FIGURE C-5A. COLOR CODE FOR S-192 RECOGNITION MAP (Fig. C-5)

TABLE C-7. WHITE SANDS S-192 PROCESSING RESULTS
THREE RATIO CASE

4 classes

Classification	Iron Mtls	Igneous	Calcareous	Clays	Other
Gnd Info					
Iron mtls	56.8	0.7	0.9	21.6	20.0
Igneous	2.0	2.0	14.0	40.0	42.0
Calcareous	23.9	2.4	11.6	34.7	27.4
Clays	46.8	0	0.3	30.8	22.1

Average Accuracy = 25.3%

6 classes

Classification	Red Alkali	Red Sediment	Precam-brian	Calcare-ous	Bolson	Dark Bolson	Other
Gnd Info							
Red Alkali	53.4	23.6	0	0	5.9	0.4	18.4
Red Sediment	2.8	27.8	1.7	2.2	6.6	34.3	24.6
Precambrian	0	2.0	2.0	14.0	8.0	32.0	42.0
Calcareous	2.0	21.9	2.4	11.6	4.4	30.3	27.4
Bolson Sediment	10.5	23.1	0	0.7	41.3	1.4	23.0
Dk. Bolson Sediment	30.8	28.2	0	0	17.3	2.5	21.2

Average Accuracy = 23.1%

TABLE C-8. WHITE SANDS S-192 PROCESSING RESULTS
FOUR RATIO CASE

4 classes

Classification	Iron Mtls	Igneous	Calcareous	Clays	Other
Iron Mtls	53.4	3.2	4.1	18.9	20.4
Igneous	6.0	16.0	22.0	26.0	30.0
Calcareous	24.9	7.8	16.7	27.9	22.7
Clays	47.3	0.3	8.0	30.8	13.6

Average Accuracy = 29.2

6 classes

Classification	Red Alkali	Red Sediment	Pre-cambrian	Calcare-ous	Bolson	Dark Bolson	Other
Red Alkali	52.5	18.6	0	2.6	7.7	1.3	17.3
Red Sediment	1.7	28.9	7.2	6.1	7.8	23.9	24.4
Precambrian	0	6.0	16.0	22.0	8.0	18.0	30.0
Calcareous	2.3	22.6	7.8	16.7	4.7	23.2	22.7
Bolson Sediment	11.9	21.0	0	3.5	48.9	0.7	23.0
Dark Bolson Sediment	33.3	28.2	0.6	12.1	13.4	0	12.4

Average Accuracy = 27.2

TABLE C-9. WHITE SANDS S-192 PROCESSING RESULTS
ELEVEN RATIO CASE

4 classes

Classification	Iron Mtls	Igneous	Calcareous	Clays	Other
Iron Mtls	61.4	1.9	2.4	16.0	18.2
Igneous	4.0	16.0	14.0	16.0	50.0
Calcareous	19.8	6.5	29.0	12.8	32.0
Clays	35.1	0.6	1.5	45.4	17.4

Average Accuracy = 38.0

6 classes

Classification	Red Alkali	Red Sediment	Pre-cambrian	Calcare-ous	Bolson	Dark Bolson	Other
Red Alkali	49.1	29.3	0.4	0.9	7.3	0.8	12.2
Red Sediment	0	39.4	3.9	4.5	10.5	15.5	26.2
Precambrian	0	4.0	16.0	14.0	8.0	8.0	50.0
Calcareous	1.7	18.1	6.5	29.0	4.8	7.9	32.0
Bolson Sediment	6.4	14.0	0	0	65.7	0	13.9
Dark Bolson Sediment	22.4	28.2	1.3	3.2	23.8	0	21.1

Average Accuracy = 33.2

eleven ratios respectively. Referring to Table C-7, the results of these analyses are summarized. With three ratios, the average correct classification is 25.3 percent for the four class and 23.1 percent for the six class cases. The numbers of the four class are quite low, and dominated by the poor recognition accuracy of the igneous Precambrian rocks (2 percent) and the calcareous rocks. Precambrian rocks are confused with the calcareous rocks and the clays because the four bands were used for the three ratio recognition, the light felsitic igneous rocks appear similar to the clays and carbonates (all have fairly flat spectra over the regions covered by the first three ratios). Only when fourth ratio is added does the separation of igneous from clays and calcareous rocks occur. The fourth ratio was one which separated carbonates and clays from light felsitic minerals because of absorption bands in the spectra of the first two materials in the bands covered by the fourth ratio. There is considerable confusion of the calcareous materials with the iron-containing materials and clays. Once again this is caused by the fact that the three ratios do not contain the bands in which one would expect separation of these materials.

In the six class case the correct recognition percentage is a bit lower, dominated again by the poor recognition accuracy of the Precambrian igneous and calcareous rocks. There also is a fair amount of misclassification between the two red (iron containing) materials and the two sediments. But the distinctions between these are fine distinctions which cannot be reliably made with only three ratios, and the three ratios used for this map, in particular.

In both cases, there is a great deal of misclassification of igneous and calcareous rocks as other. The other class consists mainly of sediments which are mixtures of clays and silica. Thus it may be expected that eroded areas of the calcareous and igneous rock units may be logically classified as the other class. Confirmation

of this fact required either low altitude photography or ground checking.

C.3.1.2.2 Four Ratio Results

As stated previously, the expected result of adding the fourth ratio would be to separate the hydroxyl and ferrous iron containing materials from the igneous and carbonate rocks. To some extent, this expectation is borne out by the empirical data. The major effect of adding the fourth ratio is to slightly improve the classification accuracy of all classes except the red sediment (and consequently red materials class in the four class results). The major effect on misclassification is to reduce the misclassification of calcareous material as clay and to reduce the misclassification of calcareous materials as Bolson sediment in the six class results. Misclassification between red alkali deposit and the red sediment and between the red sediment and Bolson sediment are reduced. Bolson sediment apparently contains substantial ferrous iron (from its gray-green color description), thus it is logical that the fourth ratio would separate this material from calcareous and ferric iron containing materials. The overall classification accuracy increases from 25.3 to 29.2 percent for the four class case and from 23.1 to 27.2 percent for the six class case when going from three to four ratios.

C.3.1.2.3 Eleven Ratio Results

By comparison with the four ratio results, the classification accuracy using thirteen ratios increases (or remains the same) for all classes except the red alkali deposit for the six class case, where increased confusion with the red sediments occurs. When comparing the results at 13 ratios compared with four ratios, many of the misclassifications decrease. However, the misclassification of Precambrian, Calcareous, and dark Bolson sediment as other, and the misclassification of red sediments and dark Bolson sediments as Bolson sediment increase.

The increase in misclassification for these classes is unexplained. Ordinarily, misclassification would be expected to decrease as more features are added to the classification process, but in cases where the features are noisy, increases in misclassifications are sometimes observed as the noisy features are added.

C.3.1.3 CONCLUSIONS

The results of the S192 processing and analysis show some promise for the S192 as a lithologic mapping device, at least for the red, ferric iron containing formations. There is evidence from ERTS results that the mapping of these formations can be accomplished with a single green/red ratio band. The relatively mediocre performance at separating this igneous Precambrian granite from the other materials could be improved by the addition of a second thermal band (to exploit the reststrahlen effects) at about 8.3-9.3 μm. Alternatively, a pass later in the day when the rocks had heated appreciably (the data processed were collected at about 0800 hrs MDT, and solar heating had not progressed far) might have produced thermal data which could have separated many of the rock types on the basis of thermal inertia. Thermal data of good radiometric fidelity would be required. These data were collected early in the Skylab mission when the S192 instrument was still being adjusted for optimum performance. As a result, the data cannot be judged as representative of what other investigations may obtain with other data sets. In addition, no visits were made to the site for ground checks of accuracy of classification. Instead, geologic maps and literature were used for assessment of what scene classes were to be mapped. Field work and/or examination of photography could change analysis and results of these data.

C.3.2 ATCHAFALAYA DATA PROCESSING RESULTS

At the outset of the processing, it was concluded that data quality would be an important issue in this phase of the effort because of the low reflectance targets and with small reflectance differences in those low reflectance targets caused by water quality differences. Accordingly, a data quality examination was begun.

Results of that investigation are shown in Table C-10. Two conditions are apparent from Table C-10 that compromise the value of this particular data set for water quality work. First, the dynamic ranges of many of the channels which penetrate the water are severely reduced, probably as a result of a conservative calibration and scaling philosophy in the production software. This low dynamic range is particularly apparent in SDO's 1, 3, 5, and 18. These SDO's are in the spectral region of maximum water penetration and all have dynamic ranges (for the whole data set, including land data) of less than 10 percent of the 256 permissible levels. This scaling reduced the utility of these data for the water quality investigation.

C.3.2.1 RESULTS OF TURBIDITY DELINEATION IN WATER

To obtain a qualitative estimate of the kinds of water turbidity which could be mapped with these data, signatures were extracted for different water quality types identified on RC-8 and S190A and B data. The means and standard deviations of two water quality types, clear (5 cases) and turbid (5 cases) are shown in Table C-11.

The very large standard deviations observed in certain channels (e.g., SDO 1, 3, and 7) of one signature, but not in the same channels in adjacent signatures of the same turbidity class illustrate the effects and magnitude of the random low-frequency noise problems in the S192 data.

TABLE C-10. S-192 DATA QUALITY
ATCHAFALAYA DATA

SDO	ERIM FORMAT T.C.*	$\lambda_1-\lambda_2$ (μm)	DYNAMIC RANGE (0.256) DATA VALUES	%	% POINT CLIPPED LOWER LIM	UPPER LIM	OTHER
1	1	.52-.56	42-55	5	0	0	
2	2	.52-.56	43-55	5	0	0	
3	3	.56-.61	34-48	6	0	0	
4	4	.56-.61	34-48	6	0	0	
5	5	.62-.67	27-42	6	0	0	
6	6	.62-.67	27-41	6	0	0	
7	7	.68-.76	44-76	13	0	0	
8	8	.68-.76	44-77	13	0	0	
9	9	.78-.88	39-61	12	0	0	
10	10	.78-.88	39-61	12	0	0	
11	11	1.55-1.75	42-58	7	0	0	218-233← 2nd Distri-
12	12	1.55-1.75	42-59	7	0	0	218-233← bution
13	13	2.10-2.35	0-7	3	0	61.6	
14	14	2.10-2.35	0-5	2	0	61.6	
17	15	1.20-1.30	34-74	16	0	0.2	
18	16	0.46-0.51	70-91	9	0	0	
19	17	0.98-1.03	29-67	15	0	0	
20	18	1.09-1.19	33-64	13	0	0	
21	19	10.2-12.5	119-146	11	0	0	
22	20	0.41-0.46	55-86	13	0	0	

*T.C. = Tape Channel

TABLE C-11. S-192 ATCHAFALAYA WATER QUALITY SIGNATURES

	SDO	22	18	1	3	5	7	21
	λ=	0.41-0.46	0.46-0.51	0.52-0.56	0.56-0.61	0.62-0.67	0.68-0.76	10.4-12.5
Clear 1 m		70.13	82.57	56.27	41.67	33.35	51.27	132.97
Σ		(4.58)	(3.18)	(21.42)	(13.25)	(1.97)	(2.49)	(4.01)
2 m		70.76	83.00	48.70	39.94	33.16	50.27	134.43
Σ		(5.11)	(2.86)	(1.59)	(1.78)	(2.02)	(3.65)	(4.49)
3 m		72.57	84.57	54.62	37.35	34.37	47.97	132.73
Σ		(5.41)	(2.84)	(39.93)	(4.80)	(7.20)	(25.73)	(4.15)
4 m		70.38	84.10	48.13	39.46	33.71	51.03	133.27
Σ		(6.40)	(3.84)	(1.92)	(2.02)	(5.59)	(15.94)	(4.61)
5 m		72.10	84.13	47.92	39.54	32.87	49.38	133.78
Σ		(5.20)	(3.13)	(1.96)	(1.86)	(1.77)	(2.95)	(4.61)
Turbid 1		73.00	86.02	51.71	44.03	37.78	59.21	137.02
		(5.54)	(3.00)	(1.59)	(2.13)	(1.84)	(2.54)	(4.72)
2		72.60	86.79	51.92	44.24	38.37	61.08	128.13
		(5.40)	(2.8)	(2.22)	(1.99)	(2.10)	(2.71)	(3.75)
3		73.97	86.10	51.56	43.73	38.21	62.56	137.86
		(4.36)	(3.17)	(1.76)	(1.64)	(2.18)	(3.38)	(4.26)
4		73.83	86.33	52.41	44.86	38.48	59.98	137.79
		(4.76)	(3.12)	(1.58)	(1.53)	(1.49)	(2.80)	(4.27)
5		73.24	87.02	52.62	43.87	37.98	61.30	135.17
		(5.30)	(3.26)	(1.77)	(2.25)	(2.34)	(3.24)	(3.58)

Composite signatures for both turbidity classes were generated using clear water training sets 2 and 5 and turbid water training sets 1-5. The composite signature statistics are presented in Table C-12.

These composite signatures were then used as input to the STEPL program (ref. 1) average pairwise probabilities of misclassification (APPM), a measure of how likely it is that a pair of targets will be confused; the resulting p.p.m.'s for each channel considered independently and the best combination of ordered spectral channels are given in Table C-13.

Low frequency noise problems, resulting in a serious circular striping pattern in the data apparent from the maps, and a limited dynamic range allow the discrimination between only high and low water turbidity levels in aquatic environments with these S192 data.

Unfortunately, no significance was found within the turbid water classes the blue spectral bands (SDO's 18 and 22) both singly, or in combination with the other visible wavelength bands. This means that there is no way in these data to separate inorganic and organic turbidity, since this would require observing a negative correlation in signal level between a blue band and one of the visible bands beyond 0.52 μm.

As a result, the only type of turbidity mapped with these S192 data was changes in the concentration of total suspended solids. The optimum turbidity mapping technique for the S192 data is then, simply, a level-sliced map of the red band.

Figure C-6 shows a color photograph of the Atchafalaya study area. The photo is an enlarged segment of an S190A photograph. The color coded turbidity map using a slicing technique on the red band 0.68-0.73 μm is shown in Figure C-7. The colors in the map denote turbidity levels from blue (clear) to red (turbid). Green areas are areas of intermediate turbidity. The water areas only are shown in Figure C-7.

TABLE C-12. COMPOSITE CLEAR AND TURBID WATER SIGNATURES FOR S-192 ATCHAFALAYA DATA

		18 0.41-0.46	22 0.46-0.51	1 0.52-0.56	3 0.56-0.61	5 0.62-0.67	7 0.68-0.73	21 10.4-12.5
Clear	m	71.43	83.56	48.31	39.74	33.02	49.83	134.10
	Σ	(5.20)	(3.05)	(1.83)	(1.83)	(1.90)	(3.35)	(4.56)
Turbid	m	73.33	86.45	52.04	44.15	38.16	60.83	137.19
	Σ	(5.12)	(3.10)	(1.80)	(1.97)	(20.26)	(3.18)	(4.27)

TABLE C-13. CHANNEL ORDERING RESULTS FOR MAPPING TURBIDITY S-192 ATCHAFALAYA DATA

Single Channel Results

λ	0.41-0.46	0.46-0.51	0.52-0.56	0.56-0.61	0.62-0.67	0.68-0.76	10.4-12.5
PPM	.427	.319	.152	.123	.095	.046	.363
Rank	7	5	4	3	2	1	6

Channel Ordering

# Channels	SDO's	APPM
1	7	.046
2	7,5	.018
3	7,5,1	.011
4	7,5,1,3	.009

FIGURE C-6. S-190A COLOR PHOTOGRAPH OF ATCHAFALAYA TEST AREA

FIGURE C-7. S-192 COLOR-CODED MAP OF ATCHAFALAYA WATER QUALITY

Land areas were edited out by slicing the 0.98-1.03 m channel to exclude the highly reflective areas. The pattern of turbidity displayed by the map corresponds qualitatively to that observed in the S190A and B photography. Quantitative checks were not made on the accuracy of recognition because of time limitations and lack of appropriate quantitative water suspended solids measurements.

C.3.2.2 CONCLUSIONS

Low frequency noise, hazy atmosphere, and the low dynamic range of the data all combined to compromise data utility. The channel ordering results show that the cleanest, widest dynamic range channel (0.68-0.73 m) was first selected for delineating water suspended solids differences even though this channel penetrates water only marginally. Data quality seems to have been the dominant factor influencing the choice of the best channel. Because of this and other data quality factors previously mentioned, the results are neither indicative of the channels to be used for water quality measurements nor the expected performance from satellite sensors.

C.3.3 BALTIMORE LAND USE CLASSIFICATION RESULTS

S192 data of the Baltimore-Washington area were processed at Honeywell to rank order the S192 spectral bands for Land Use mapping and to demonstrate the classification accuracy of Anderson Level II Land Use classes obtainable with varying numbers of spectral bands. The classes used in the recognition operation are listed in Table C-14. The class numbers correspond to the Anderson Level II numbering system with the exception of classes 81 and 82, which are second samples of classes 11 and 12.

The rank ordering of spectral features was performed using the mapping error as a criterion. This parameter is analogous to the probability of misclassification for maximum likelihood classifiers. The results of the channel ordering are shown in Table C-15.

TABLE C-14. RECOGNITION CLASSES FOR S-192 BALTIMORE DATA

Code	Class Number	Class
1	11	Residential
2	12	Commercial
3	13	Industrial
4	15	Transportation
5	16	Institutional
6	81	High Density Residential
7	82	High Density Commercial
8	19	Open and Others
9	21	Cropland
10	22	Orchards, Fruit Bush, Vineyard, etc.
11	41	Heavy Crown Cover Forestland
12	42	Light Crown Cover Forestland
13	31	Cloud Shadows
14	51	Streams and Waterway
15	52	Lake
16	53,54	Reservoirs and Bay
17	32	Cloud

TABLE C-15. S-192 PERFORMANCE ORDERING
BALTIMORE-WASHINGTON DATA

SDO NUMBER	WAVELENGTH (μm)	RANK
21	10.2 - 12.5	1
9	0.78 - 0.88	2
22	0.41 - 0.46	3
13	2.10 - 2.35	4
7	0.68 - 0.76	5
18	0.46 - 0.51	6
1	0.52 - 0.56	7
5	0.62 -	8
17	1.2 - 1.3	9
19	0.98 - 1.03	10
11	1.55 - 1.75	11
20	1.09 - 1.19	12
3	0.56 - 0.61	13

The results of the channel ordering show that the thermal band is most useful at separating the Level II land use classes. This is because of the urban and non-urban classes and the overlight time near noon when the temperature differences between urban and non-urban areas are large. The second selected band was 0.78-0.88 μm a band in which the vegetation has high reflectance and the water has low reflectance. The third band chosen was the blue band 0.41-0.46 μm where the urban categories are more highly reflective than the vegetation. The fourth channel selected was 2.1-2.35 μm where urban areas are bright, and water and vegetation dark. The close correlation between the channel ordering results for the S192 data and the aircraft scanner data should be noted. The only channel different in the top four is the 2.1-2.35 μm channel replacing the 0.62-0.70 μm band of the aircraft data. But as previously noted, the red band seemed relatively noisy in other data sets, and probably is in the Baltimore data set also. This may account for its relatively low order in the channel selection. Table C-16 compares the ordering of channels of S192 data with those of the aircraft data discussed in Section 3.

C.3.3.1 PRELIMINARY CLASSIFICATION RESULTS

Several types of classification were performed on the S192 data. First, training was done to recognize five classes of land use, roughly corresponding to Anderson Level I land use. The k-class classifier was used to recognize the classes using the best four, seven, and all thirteen channels of S192 data. The results (see Tables C-17 through C-19) show improvement in the classification accuracy from 68.7 percent to 72.4 percent as the number of channels is increased from 4 to 13. Probably as a result of spectral variability in the class, the agriculture recognition remains the lowest of all of the five classes for all three channel sets. The urban class is consistently the best recognized and if we discount mis-

TABLE C-16. COMPARISON OF S-192 and AIRCRAFT DATA CHANNEL ORDERING - BALTIMORE DATA

Order	S-192 Channel	Aircraft Channel
1	10.2 - 12.5	1.0-1.4
2	0.78 - 0.88	0.41-0.48
3	0.41 - 0.46	9.3-11.7
4	2.10 - 2.35	0.67-0.94
5	0.68 - 0.76	0.62-0.70
6	0.46 - 0.51	0.50-0.54
7	0.52 - 0.56	2.0-2.6
8	0.62 - 0.67	0.46-0.49
9	1.2 - 1.3	0.58-0.64
10	0.98 - 1.03	0.48-0.52
11	1.55 - 1.75	0.52-0.57
12	1.09 - 1.19	0.55-0.60
13	0.56 - 0.61	

TABLE C-17. S-192 CONFUSION MATRIX RESULTS FROM BALTIMORE-WASHINGTON DATA

CLASSES

1. Agriculture
2. Forest
3. Water
4. Urban
5. High Density Residential and Commercial

CLASSIFIER

GROUND	1	2	3	4	5
1	51.42	14.69	11.84	1.05	20.99
2	6.30	64.57	27.56	0.79	0.79
3	11.88	21.78	64.36	0.99	0.99
4	3.06	0.00	2.38	82.31	12.24
5	29.94	1.13	3.95	1.69	63.28

Average Classification Accuracy = 68.66

Features Used = Top 4 10.2-12.35, 0.78-0.88, 0.41-0.46, and 2.1-2.35

TABLE C-18. S-192 CONFUSION MATRIX RESULTS
FROM BALTIMORE-WASHINGTON DATA

CLASSES

1. Agriculture
2. Forest
3. Water
4. Urban
5. High Density Residential and Commercial

CLASSIFIER

GROUND	1	2	3	4	5
1	51.12	16.19	8.85	2.25	21.59
2	11.81	63.78	23.62	0.79	0.00
3	11.39	20.30	65.35	2.48	0.50
4	0.68	0.00	0.68	98.64	0.00
5	29.32	2.82	3.39	0.00	64.41

Average Classification Accuracy = 65.18

Features Used = Top 7, Top 4 plus 0.68-0.76, 0.46-0.51, and 0.52-0.56

TABLE C-19. S-192 CONFUSION MATRIX RESULTS
FROM BALTIMORE-WASHINGTON DATA

CLASSES

1. Agriculture
2. Forest
3. Water
4. Urban
5. High Density Residential and Commercial

CLASSIFIER

GROUND	1	2	3	4	5
1	56.67	12.59	12.44	0.15	18.14
2	3.94	70.87	22.83	0.70	1.57
3	9.90	18.32	71.29	0.50	0.00
4	0.68	0.00	0.34	97.62	1.36
5	31.64	1.69	1.13	0.00	65.64

Average Classification Accuracy = 72.39

Features Used = all 13

classifications of urban as high density urban, this is even more so — the recognition accuracy approaches 100 percent with 7 channels and is always above 90 percent. The slight decreases in recognition accuracy of agriculture and forest classes are probably not significant in view of the small sample used for assessing classification accuracy.

Even at the thirteen channel level, persistent misclassification of Agriculture as Forest, Water, High Density Residential occur. Also Water is misclassified as Forest, and High Density Urban is misclassified as Agriculture. Some of the misclassification involving Agriculture may be the result of bare soil areas in the Agriculture areas being confused with High Density residential and vice versa. The Agriculture-Forest misclassification may be understood since dense green vegetation is involved in both cases. The misclassification of water as forest cannot be explained, since the two have radically difference reflectance in the near IR bands around 1 μm. In spite of these difficulties, the results show a high classification accuracy overall for the 13 channel case.

C.3.3.2 FURTHER CLASSIFICATION RESULTS

Classification was performed using the K-class classifier, the seventeen training sets shown in Table C-14, and the thirteen spectral channels. Results of the classification are shown in Table C-20. Overall classification accuracy of 42.1 percent was achieved. Then a sequential approach to classification was tested, as diagrammed in Figure C-8. By separating scene materials into broad classes, then further subdividing those classes using other channel sets, an improvement to 53.14 percent accuracy was obtained. Confusion matrix results are presented in Table C-21.

One final improvement was performed on the 13 channel sequential classification experiment. The single point misclassifications were filtered out by accepting the second most likely decision. The filtering procedure was performed as follows.

TABLE C-20. CONFUSION MATRIX FOR BALTIMORE S-192 PROCESSED DATA

	1/	2/	3/	4/	5/	6/	7/	8/	9/	10/	11/	12/	13/	14/	15/	16/	17/
1/	62.33	3.82	.86	1.17	4.69	.09	.00	4.19	7.03	.81	6.80	6.26	.72	.05	.[illegible]	.27	.90
2/	23.89	22.12	4.42	14.16	15.93	2.65	.00	3.54	5.31	.88	1.77	4.42	.05	.00	.00	.00	.88
3/	4.[illegible]	10.23	34.50	21.35	11.40	7.02	.88	.00	.58	.29	.00	.00	.58	.00	.00	1.46	7.60
4/	[illegible]	18.42	11.58	47.37	10.00	2.11	1.05	2.63	.53	.53	.00	1.05	1.05	.00	.00	.00	.53
5/	[illegible]	6.57	.73	8.94	27.74	1.09	.55	11.68	6.75	.91	.36	2.19	.91	.55	.00	.36	1.28
6/	31.32	12.88	4.17	9.85	14.02	12.50	3.03	4.55	2.27	.00	.00	3.03	.38	.00	.00	.00	1.52
7/	9.79	4.90	.00	19.58	2.10	5.99	55.94	.00	.00	.70	.00	.00	.00	.00	.00	.00	.00
8/	30.19	3.08	.32	2.11	4.22	.00	.00	31.82	21.10	1.62	1.45	1.14	.00	.00	.00	.32	2.60
9/	25.17	.19	.00	.89	1.86	.08	.00	13.69	40.65	2.17	6.83	7.84	.08	.00	.00	.00	.54
10/	10.00	.00	.00	.00	.00	.00	.00	3.33	33.33	53.33	.00	.00	.00	.00	.00	.00	.00
11/	27.59	.15	.00	.23	.15	.00	.08	.91	6.67	.34	51.13	11.75	.38	.04	.00	.08	.45
12/	24.84	.00	.00	.32	4.19	.00	.00	2.90	12.90	.65	10.00	41.29	1.29	.00	.00	.32	1.29
13/	6.87	.00	.00	1.53	2.29	.76	3.05	.00	.00	.00	.76	1.53	76.34	.00	.00	.76	6.11
14/	1.10	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	40.66	39.67	2.20	16.48	.00
15/	.00	4.76	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	28.57	23.81	4.76	28.10	.00
16/	2.49	.28	.00	.00	.00	.00	.68	.00	.00	.00	.23	.45	56.33	5.66	.00	33.48	.45
17/	12.95	.00	.00	.00	.00	.00	.00	.00	1.44	.00	4.32	.00	.00	.00	.00	.00	81.29

Classification Accuracy Mean = 42.131

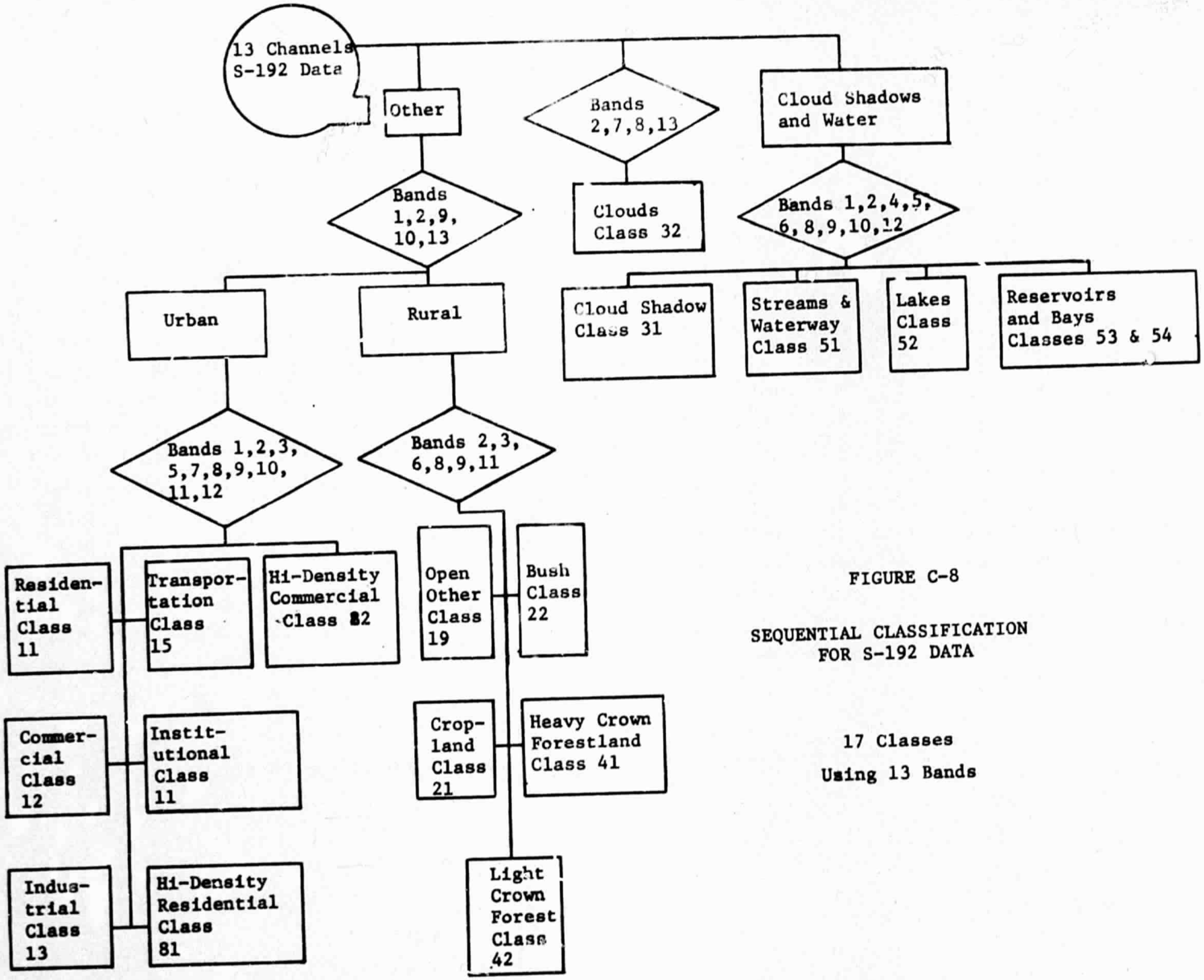

FIGURE C-8

SEQUENTIAL CLASSIFICATION
FOR S-192 DATA

17 Classes
Using 13 Bands

TABLE C-21. CONFUSION MATRIX RESULTS FOR BALTIMORE S-192 DATA

	1/	2/	3/	4/	5/	6/	7/	8/	9/	10/	11/	12/	13/	14/	15/	16/	17/
1/	53.54	.77	.14	1.44	1.04	3.06	.00	5.50	5.68	2.25	10.68	15.86	.00	.00	.00	.05	.00
2/	17.70	40.71	6.19	15.04	2.65	5.31	.00	1.77	2.65	.00	.88	7.08	.00	.00	.00	.00	.00
3/	4.39	2.63	61.40	7.89	1.75	19.88	1.75	.00	.00	.00	.00	.00	.00	.00	.00	.29	.00
4/	8.42	4.74	4.74	67.89	.53	13.16	.00	.00	.00	.00	.00	.00	.00	.00	.00	.53	.00
5/	23.36	3.28	1.09	7.85	41.97	4.56	.91	5.84	7.12	.00	.18	2.92	.00	.55	.00	.00	.36
6/	32.95	3.70	3.41	7.20	4.55	40.91	3.41	.38	.28	.00	.00	3.03	.00	.00	.00	.00	.00
7/	3.50	1.40	.00	1.40	.00	2.80	90.21	.00	.00	.00	.00	.70	.00	.00	.00	.00	.00
8/	16.07	2.76	.00	2.27	8.93	.65	.00	57.14	7.79	.32	1.79	1.14	.00	.00	.00	.00	1.14
9/	4.03	.08	.00	1.28	2.01	.89	.00	2.75	76.18	1.28	5.34	5.19	.00	.04	.00	.00	.93
10/	.00	.00	.00	.00	.00	.00	.00	.00	3.33	96.67	.00	.00	.00	.00	.00	.00	.00
11/	2.01	.00	.00	.38	.19	2.80	.27	.38	2.39	.67	87.23	3.03	.00	.11	.00	.00	.64
12/	8.39	.00	.00	.65	1.61	9.58	.00	2.26	10.97	.00	2.58	63.55	.00	.00	.00	.32	.00
13/	1.82	.00	.91	2.73	.00	.91	.00	.00	.00	.00	.00	3.64	88.18	.00	.00	1.82	.00
14/	5.49	.00	.00	.00	.00	14.29	1.10	.00	.00	.00	.00	.00	.00	72.53	.00	6.59	.00
15/	.00	.00	4.76	.00	.00	9.52	.00	.00	.00	.00	.00	.00	.00	.00	71.43	14.29	.00
16/	1.81	.00	.00	.00	.00	9.28	2.26	.00	.00	.00	.23	.90	.00	3.62	.00	81.90	.00
17/	.83	.00	.00	.00	.00	.00	.00	.00	3.31	.00	1.65	1.54	.00	.00	.00	.00	92.56

Classification Accuracy Mean = 69.647

. a b c . . .

. d x . . . .

. . . .

When attempting to determine the class of point x, if the highest decision number from K-class is the same as in a, b, c, or d, it is used to point x. However, if the highest decision number, indicating the most probable class, is not in a, b, c, or d, the next most likely class or next highest number is checked. By cleaning up the thematic map in this manner, the classification accuracy is increased to 69.64 percent, as shown in Table C-22. Note that with these advanced procedures that the average recognition accuracy for the seventeen class case, representing Anderson Level II classification, is nearly as good as the Level I recognition using the K-class classifier in a one pass recognition operation.

The area processed is shown in Figure C-9, and a color coded map of the recognition, with legend, is shown in Figure C-10.

TABLE C-22. CONFUSION MATRIX FOR BALTIMORE S-192 DATA

	1/	2/	3/	4/	5/	6/	7/	8/	9/	10/	11/	12/	13/	14/	15/	16/	17/
1/	48.76	1.44	.32	1.44	2.88	.45	.00	5.36	5.45	2.39	11.04	17.17	2.75	.09	.09	.36	.00
2/	31.36	12.39	6.19	17.70	9.73	5.31	.00	2.65	2.65	.00	.88	7.96	.88	.00	.88	.88	.00
3/	3.80	2.92	36.26	25.15	3.22	6.43	3.51	.00	.00	.00	.00	.29	3.80	.58	6.43	7.50	.00
4/	8.95	9.47	14.21	44.74	3.68	4.74	4.21	.00	.00	.00	.00	.00	1.58	.53	3.16	4.74	.00
5/	35.58	5.84	.55	12.04	20.99	2.01	.73	6.20	7.48	.00	.36	3.47	2.55	.36	1.09	.36	.36
6/	39.77	9.85	6.06	8.71	5.68	14.77	7.20	.38	.76	.00	.00	2.65	2.65	.00	.38	1.14	.00
7/	6.29	2.10	.00	6.29	.00	5.59	79.72	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
8/	16.88	1.70	.00	1.79	10.71	.00	.00	28.57	32.63	2.11	2.27	1.30	.65	.00	.16	.00	1.14
9/	3.59	.15	.00	1.25	2.72	.00	.00	10.05	60.28	1.97	8.36	9.83	.91	.00	.00	.00	.91
10/	.00	.00	.00	.00	.00	.00	.00	.00	20.00	76.67	.00	3.33	.00	.00	.00	.00	.00
11/	1.39	.04	.00	.34	.19	.00	.23	.87	3.73	1.52	69.03	18.93	2.45	.19	.04	.34	.64
12/	7.74	.32	.32	.65	2.26	.00	.00	4.52	18.06	.00	6.13	50.00	7.42	.00	.00	2.58	.00
13/	.75	.00	2.26	6.77	.00	.75	1.50	.00	.00	3.01	.00	3.76	3.76	4.51	3.01	69.92	.00
14/	5.49	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1.10	58.24	9.89	25.27	.00
15/	.00	.00	.00	.00	.00	4.76	.00	.00	.00	.00	.00	.00	.00	4.76	52.38	38.10	.00
16/	1.58	.00	.00	.00	.00	.00	.45	.00	.00	.00	.23	.90	.45	10.41	8.82	77.15	.00
17/	.00	.00	.00	.00	.00	.00	.00	5.04	4.32	.00	5.04	4.32	.00	.00	.00	.00	81.29

Classification Accuracy Mean = 47.9407

FIGURE C-9. S-190A COLOR IR PHOTO OF BALTIMORE TEST SITE

ORIGINAL PAGE IS
OF POOR QUALITY

FIGURE C-10. S-192 COLOR-CODED RECOGNITION MAP OF BALTIMORE TEST AREA

ORIGINAL PAGE IS
OF POOR QUALITY

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